URBAN POLARIZATION IN THE UNITED STATES OVER TIME AND SPACE

by

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ABSTRACT

The Polarization Hypothesis has been a fruitful area of research in urban sociology over the past several decades. Polarization itself is a multifaceted phenomena, dealing with the middle class, the poles of the income distribution, spatial polarization/segregation and changes over time. As of yet, the interaction of the multiple facets and their definition has not been addressed. This manuscript uses a single, geographically fine grained, time-series dataset to investigate the definitional boundaries of polarization measurement from 2002-2011 in urban areas in the United States. Methods include Hierarchical Linear Models and Cusp Catastrophe models to explicitly deal with time. Multiple dependent variables are used to check and see if key assumptions of the Polarization Hypothesis hold true when dealing with each facet (income distribution, and spatial) of polarization over time in a large scale statistical analysis.

This manuscript is dedicated to my perfect wife Lindsay and our children Gideon, Jackson, Lillian, Miriam, Sophia and Theresa, because they deserve to get something out of this slog.

“In science, when human behavior enters the equation, things go nonlinear. That's why Physics is easy and Sociology is hard.” Neil deGrasse Tyson, Twitter 5 Feb 2016

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INTRODUCTION

Saskia Sassen's book *The Global City* started a research project that has spanned decades, multiple methods and has become popular in policy discussions. One aspect of that book was the Polarization Hypothesis, which put forward the idea that economic structural changes accompanying the decline of manufacturing industries changed the balance of low, middle and upper income groups.

This hypothesis has been substantially critiqued, and has found support. This substantial body of supporting research, however, has yet to take a close look at a key underlying aspect of the Polarization Hypothesis: time. Implicit in the hypothesis is a change over time. Most studies have simply compared data at two points of time in a single city. This is the first study to take multiple annual snapshots of data to look at the dynamics of polarization and how polarization changes from year to year across urban areas in the United States.

As Sassen and others state, the key driver is change in the economic structure. Also noteworthy, however, is the fact that that changes in economic structure go beyond the well-documented transition toward a service-centered economy, and must also be evaluated in the context of an increasingly connected global economy. Curiously, this connection between the local and the global is all but absent from the literature on the Polarization Hypothesis.
This paper will account for the global connections of U.S. cities in its analysis of the multifaceted relationship between polarization, economic structure and network position over time, while also allowing for variation across different spatial scales. This is an attempt to utilize new techniques for dealing with complex systems such as global networks and urban phenomena.

Among the goals of this paper is to reveal patterns that show the geographic constraints of the Polarization Hypothesis, and display the tools for studying complex systems.

The primary argument of this paper is that polarization is a complex process with multiple facets and has not been well defined. Previous researchers have attacked the issue from multiple angles, all using the term polarization, but in markedly different ways. By using a single dataset to compare the different measures of polarization future researchers will understand the nuance of polarization and be able to be more precise in their definition of polarization.

BACKGROUND

Income Polarization

Sassen's influential book on Global Cities defined polarization as "a shift in the job supply and polarization in the income distribution and occupational distribution of workers" (1991, 6). This Polarization Hypothesis identifies a causal link between income inequality and the economic structure of a city. The shift from industrial production to a service-centered economy is described as a catalyst that not only generates income inequality, but also polarization, which is a shift to extreme positions both in terms of the income distribution and the spatial location of people along that income distribution.

Polarization denotes divergence to the extreme, a dissimilarity that goes beyond simple inequality (Esteban and Ray 1994; Sassen 1991). These extremes can be captured in a few different ways, including the gulf between the affluent and the poor (Reardon and Bischoff 2011; Baum 1997; Mollenkopf and Castells 1991), or the change in the number of people in different income categories over time (Wilson 1987). The polarization itself indicates that there is more similarity within the groups than between them, forming pockets of distinct subgroups of people with different life outcomes and quality of life options.

One of the ways that polarization manifests itself in data is the shift from a normal income distribution to a bi-modal distribution. In a normal distribution, the majority of the population is represented in the middle of the graph, representing the middle class. In a polarized distribution, however, there are multiple peaks, one at each end of the graph, indicating that most of the population is represented at the ends of the income spectrum rather than the middle.

The cause of this shift from a normal to bi-modal income distribution is the rise of advanced producer service (APS) firms. These service firms specialize in management functions that drive the global economy, and thereby are the command and control points for global business and the linkages between cities (Castells 2011; Sassen 1991; Goerzen, Asmussen, and Nielsen 2013). APS firms are exemplified by the finance, insurance, and real estate (F.I.R.E.) sectors of the economy, taking on a number of specialized skills and providing them to other businesses. These specialized firms have offices all over the world and can connect or minimize the costs of coordinating global production. The rise of these services occurred in tandem with the development of global telecommunications (i.e., the internet) allowing for faster transmission of information around the globe and the ability of business management to be divorced from locational constraints (Castells 2011). This locational divorce allows business headquarters to maintain control of subsidiaries and regional branches around the world; it also allows for manufacturers to leave urban areas because they no longer need a labor market diverse enough to house the skills that they have outsourced to the APS firms. This freedom allows the manufacturing business to move from high-priced urban areas to more cost-effective locations (i.e., suburbs or offshore sites), taking with them the employment opportunities for many of the middle and working classes (Krugman 1990; Sassen 1991; Lang 2003).

The APS firms, however, need a highly skilled work force and access to telecommunications services, which causes them to cluster in urban areas (Sassen 1991; Goerzen, Asmussen, and Nielsen 2013; Amin 2000). The growth and clustering of APS firms—combined with their need to attract highly skilled laborers—lead to a rise in incomes, which in turn causes the high-end of polarization in the urban area. Furthermore, the middle class has the necessary resources to follow the manufacturing firms out of the urban area, leading to a decrease in middle class population and, ultimately, the abandonment of the working class to consumer-based service industries like restaurants, dry cleaners, and dog walkers (Abrahamson 2004).

The research on polarization is primarily composed of narrowly focused case studies on individual cities, including Helsinki (Vaattovaara and Kortteinen 2003), Sydney (Baum 1997), Cape Town (Borel-Saladin and Crankshaw 2009), Oslo (Wessel 2000), the Randstad (Hamnett 1996; Burgers 1996; Kempen 1994), Toronto (Walks 2001), New York, London, Tokyo (Sassen 1991), Singapore (Baum 1999) and Hong Kong (Chiu and Lui 2004). The case studies provide mixed evidence for the Polarization Hypothesis, with clear evidence of polarization occurring in Oslo, Sydney and Hong Kong, and only weak or mixed evidence in Helsinki and the Randstad. The other studies find more support for the competing theory of professionalization than for polarization.

Hamnett (1994, 405) critiqued the Polarization Hypothesis as being 1) vague and ill-defined, 2) in denial of other explanations, such as professionalization, and 3) overly influenced by immigrant cities such as New York. Hamnett's first point about polarization being ill-defined refers to whether absolute or relative change in the middle class constitutes polarization. If absolute change is required, then there must be a decrease in the middle class, or a growth in the ends of the income distribution large enough to generate a bi-modal distribution. A relative change would mean that polarization exists if the tails of the income distribution grew faster than the middle, not creating a bi-modal distribution, but starting down a path that would develop it over time.

The second critique is that the phenomena typically associated with the Polarization hypothesis are better explained as a process of professionalization. Proponents of the professionalization hypothesis argue that the economic shift to a service-based industry is creating a new middle class out of managers and those with professional skills. A key component of this professionalization hypothesis is that the welfare state will mitigate polarizing influences and thus maintain a normal income distribution. In Cape Town, Singapore, and Toronto, there was little evidence of polarization found, and much of its absence was attributed to the work of the welfare state (Hamnett 1994; Borel-Saladin and Crankshaw 2009; Hamnett 1996; Baum 1997).

The final critique Hamnett leveled at the Polarization Hypothesis is its over reliance on the cases of New York, London and Tokyo, which he does not view as representative of Global Cities. This critique is one that could be applied to any of the case studies, since the sample size for each is limited to one. It wasn't until 2012 the first large-scale statistical analysis was conducted on the Polarization Hypothesis, an analysis that produced mixed results. The authors tested the idea that a city's centrality in the global economy would be correlated with occupational and income polarization. They found that centrality was positively related to income inequality, but only when there were high levels of recent immigration (Timberlake et al. 2012).

Based on this literature, I will test the following three hypotheses:

H1: Polarization in urban areas exists, and it can be seen growing over time.

H2: Polarization has a positive correlation with F.I.R.E. employment.

H3: Polarization has a negative correlation with Manufacturing employment.

<u>Polarization and the Global Economy</u>

A city's integration with the global economy and its effects on city structure were discussed by Friedmann, who said that "World city formation brings into focus the major contradictions of industrial capitalism - among them spatial and class polarization" (Friedmann

1986, 76). The causes of this polarization at the metropolitan level are income gaps between the high and low skilled workers, migration to the metro area and structural changes in the employment landscape. These issues in turn are developed by formation of a World City or Global City, characterized as such due to the connections that it has with other cities around the world, connections that are formed primarily by APS firms' management of complex global operations (Sassen 1991; Taylor et al. 2002; Zachary Neal 2013).

These connections create a hierarchy of cities across the globe, and the cities at the top of the hierarchy are those that command and control the capital flowing to the rest of the world (Alderson and Beckfield 2004; Sassen 1991; Friedmann 1986).). The connections themselves are made up through the channels of flowing capital, from headquarters to back offices and subsidiaries or regional headquarters. An individual city can be articulated within the World Network of Cities (WNC) based on how many connections are emanating from it (power), the number of connections coming into it (prestige) or how close the city is tied to the other cities in the network (position) (Alderson and Beckfield 2004).

The network itself is expected to be a dynamic system, with cities rising and falling in the hierarchy over time in accordance with economic changes (Alderson and Beckfield 2004). Such changes should have an attendant impact on polarization within a city. If a city falls in rank, it indicates that capital is flowing through other cities and either the number of APS employees should decrease or their incomes decline. This generates another hypothesis to test:

H4: Network position, power and prestige have a positive correlation with polarization.

<u>Polarization and Space</u>

The Polarization Hypothesis describes not only changes to the income distribution, but also the spatial organization of the city (Sassen 1991; Walks 2001). The preference of people to live near similar individuals has been well documented (Schelling 1971). Similarity in residence location has been tied to political ideology (Bishop 2009), racial makeup (Krysan et al. 2009; Krivo, Peterson, and Kuhl 2009) and education (Bayer et al. 2007). APS employees share a combination of high income, specialized skills, and/or advanced education, all of which are factors in clustering behavior.

In clustering together, the APS employees also comprise a key driver in the gentrification process (Sassen 1991), which is described as the more affluent increasing rents to a point that the working class cannot afford them (Freeman and Braconi 2004; Lees 2008; Krysan et al. 2009; Krivo, Peterson, and Kuhl 2009). Experiments with agent-based models on locational preference show majority populations spread out from their original cluster, forcing minority groups to form more ephemeral clusters as old clusters are encroached upon by the majority (Crooks 2010), which is consistent with the literature on gentrification.

This displacement of households changes the spatial dispersion of wealth as well as the nature of community ties within an urban area. This shift is part of what Jane Jacobs chronicled in her book the Death and Life of Great American Cities (Jacobs 1961). Part of this disruption is the changing local economic landscape away from small neighborhood businesses to chain stores catering to gentrifiers and patterns demarcated by high levels of consumption (Sassen 1991; Butler and Lees 2006; Abrahamson 2004).

Gentrification studies have similar methodological problems to the polarization studies; they are primarily case studies looking at small areas and not able to empirically generalize their findings. It is also difficult to generalize a qualitative shift from a state of nongentrification to a state of gentrification. Friedman (2004), for example, notes that the housing churn of disadvantaged households slowed as gentrification occurred, not sped up as expected. But this slowing does not signal a change to a state of gentrification.

To address these issues, I will look for the following patterns:

H5: Gentrification should increase with F.I.R.E. or Centrality increases.

H6: Segregation (as hot spots or area) should increase with increase of F.I.R.E. jobs or centrality or polarization.

Another issue dealing with space and the Polarization Hypothesis is that of geographic scale. Sassen's analysis of New York City focused solely on Manhattan (1991). Other polarization studies are unclear about the actual boundaries used to delineate their cities (Wessel 2000; Baum 1997). This issue goes back to Hamnett's (1994) critique of the Polarization Hypothesis' being ill-defined. Spatial scale, while often over looked in sociology (Tickamyer 2000; Lobao, Hooks, and Tickamyer 2007) has an effect on the type of analysis and results those analyses provide (Hipp 2007; Voss 2007; Porter and Howell 2012). Fainstein (2000) found that when polarization is examined in larger areas, such as a metropolitan region, the gulf between the top and bottom 20 percent of the income distribution is not as great as when observation is limited to within municipal boundaries.

Central cities are not isolated, but part of larger integrated geographic and economic units (Benner and Pastor 2011; Florida, Gulden, and Mellander 2008; Ross 2009; Zachary Neal 2013). With over 70 years' worth of investments in transportation infrastructure, as well as the development of suburbs, strip malls, and office parks, formerly distinct urban areas have grown into large, complex systems (Vicino, Hanlon, and Short 2007; Nelson and Lang 2011; Lang 2003; Garreau 1991). Within a single urban area, there are often multiple cores, where cities have grown together creating a polynucleated urban fabric (Batty 2001; Meijers 2005; Kloosterman and Lambregts 2001; Gordon and Richardson 1996). Commuting patterns between these areas indicate that large geographic areas are tightly linked (Guthrie 2007; Nelson and Lang 2011; Clark and Kuijpers-Linde 1994; Dessemontet, Kaufmann, and Jemelin 2010).

This expansion of urban areas and the movement of jobs to suburbs and exurbs may mean that Sassen's Polarization Hypothesis is an artifact of the geographic scale of analysis. The primary driver of polarization is the shift away from manufacturing which takes away the jobs of the middle class. If the manufacturing firms move outside the central city but remain in the metro area, there should be little polarization, since middle class employment is still within commuting distance. Another possibility is that the middle class moved with the manufacturing employment to the suburbs, creating localized polarization but not effecting the polarization of the metro area.

This idea leads to my next hypothesis that:

H7: The model fit of polarization shouldn't change at different spatial scales.

Polarization and Time

One of the commonalities in Polarization Hypothesis studies is that they deal with change over time. In all of the case studies, measurements were taken at two time points and compared to see if polarization was occurring. The benefit of looking at differences over time is that it can capture some of the complexity of cities. Cities, being composed of individuals, firms, governments, and other actors, are a social structure generated out of the actions of multiple actors, similar to globalization itself (Urry 2007; Urry 2005; Byrne 2002; Castellani and Hafferty 2009).

By observing complex systems over multiple points in time, it is possible to observe the stability of complex phenomena such as polarization (Butner et al. 2015). It is also possible, then, to expand the theory beyond the existence of polarization and determine how quickly or slowly polarization is occurring.

According to Sassen, the increase in APS firms generates income and spatial polarization, and Friedman says that position in the WCN increases polarization as well. An unasked question is what happens when APS firms decrease, or WCN position changes. If the relationship between these predictive variables is linear, then polarization should decrease. Another possibility could be that polarization will not decrease due to the complex interactions that comprise urban areas. Instead, urban areas exist in a combination of states of high and low polarization, and that the rate of polarization is modified by APS firms and global position.

The movement between high and low states is the key difference between segregation and polarization (Esteban and Ray 1994). Income inequality and segregation have always existed in urban areas and have been correlated with race, ethnicity and occupation (Reardon and Bischoff 2011; Lees 2008). Polarization and gentrification are dynamic issues, exemplified by changes over time. Therefore, my final hypotheses are:

H8: Urban areas have multiple stable states of polarization.

H9: Stable states are modified by connection to the global economy and APS employment growth.

DATA

Networks

The first groups of data deal with the relationship between cities, which is the network that creates urban hierarchies. For the global urban hierarchy, data come from the LexisNexis Corporate Affiliates database, which contains information on the location of headquarters, subsidiaries, and branches of firms throughout the world. Similar data have been used previously to determine the position of cities in the global hierarchy (Alderson and Beckfield 2004).

The precise locations contained in this database will also allow for aggregation at different spatial scales. One of the weaknesses of previous research using firm location data is that it was limited to headquarters located in specific notable cities like London, New York City, or Tokyo but not their surrounding areas (Taylor, Hoyler, and Smith 2012; Derudder and Witlox 2007). According to Sassen's theory on global cities, this should not be an issue because APS firms will locate in the center of the prominent cities (Sassen 2001). Utilizing geographic information systems (GIS) data, the connections between each area have been aggregated to the appropriate scale. This type of analysis will help to mitigate the problems of scale, where models fit at one scale don't generalize to other scales. This problem is referred to as the Modifiable Areal Unit Problem (MAUP).

This same LexisNexis data can be used to generate both international and national corporate hierarchies. LexisNexis Corporate Affiliates database contains information on the headquarters and subsidiary locations of firms. The list of firms will come from Fortune's Global

500 list, which has been used previously (Alderson and Beckfield 2004). The difference between these data and those used by Alderson and Beckfield (2004) is that the list of firms will come from the Global 500 from the years 2002 – 2011, whereas the Alderson and Beckfield data cover only the year 2000.

The network and hierarchy of the World City System has been analyzed in two primary ways: interlocking cities and social network analysis. One of the most active research groups is the Global and World Cities (GaWC) research network which uses interlocking directorate network analysis to define the relationships between cities. In this method, the GaWC researchers selected a list of potential World Cities and link cities together through headquarter-subsidiary relationships. For example, if city A had a headquarters and city B had a branch of the same firm, then city A and B would be connected. These links create a matrix of values, indicating the strength of the ties from each city to every other city. This matrix could also be subdivided on the basis of APS subindustry (i.e., banking, insurance, advertising) (Taylor et al. 2002; Taylor and Walker 2001; Taylor 2004).

Taylor and GaWC have expanded the analysis to look at the interlocks of noneconomic agents like NGOs (Toly et al. 2012), media and architectural firms (Taylor 2005). In all of their work they have generated typologies to classify cities. The first classification is based solely on the economic portion of the network (Toly et al. 2012).

First are the Alpha Cities (Beaverstock, Smith, and Taylor 1999).), which form the top of the world cities hierarchical system. New York, London, Paris, and Tokyo are consistently at the top of the list of Alpha Cities (Friedmann 1986; Taylor et al. 2002; Alderson and Beckfield 2004). These cities have the greatest number of multinational firms across all of the APS sectors (Taylor 2004), they have the most connections and according to social network analysis, and are the most central nodes in the world city network (Smith and Timberlake 2001; Alderson and

Beckfield 2004). These core cities are found in core nations replicating, in part, international inequalities in power (Beaverstock, Smith, and Taylor 1999).

The next tier of cities is classified as Beta Cities, and, though they do not have the same number of international firms as the alpha cities, they are important regional hubs, or specialized in one or two sectors (Beaverstock, Smith, and Taylor 1999, 455). While this category of cities is dominated by the same geographic regions as the alpha cities, it also features the additions of Sao Paulo and Moscow, both of which are located in BRIC countries and are key cities in the semiperiphery (Beaverstock, Smith, and Taylor 1999).

The Gamma Cities are at the low end of the world city hierarchy, but are still connected to the global flows of information and capital. Similar to beta cities, they generally only have one industrial sector in which they specialize.

When looking beyond the solely economic networks, a different typology emerges with New York and London joined by Paris, Los Angeles, and San Francisco as global cities with economic, cultural and political power (Taylor 2005). Other cities fill niche roles, focusing on one industry in particular or articulator cities that are central to specific subnetworks of cities. All these analyses show the complexity of the network of world cities and the inequalities that exist within the hierarchical structure. The multinetwork analysis, in particular, illustrates the polarization that exists between world cities since it organizes the cities into groups across multiple variables (Taylor 2005).

While the interlocking city model has produced insightful research, social network analysis offers other avenues for exploring network relationships. The Social Network Analysis (SNA) approach to understanding the structure of the world cities network begins with some different fundamental assumptions. First is the assumption of which cities or firms should be included in the analysis. In the interlocking matrix approach, experts chose the cities and the firms that would be studied as part of the analysis. SNA, in contrast, captures a wide range of data on firms and cities and is not constrained by the same limitations of size. This difference leads to the description of the interlock approach as a "network of world cities" and SNA as a "world network of cities" (Beckfield and Alderson 2006, 900). The two primary sources of data used in the SNA approach are airline flights (Smith and Timberlake 2001; Z Neal 2013; Mahutga et al. 2010; Derudder and Beaverstock 2008) and corporate hierarchy locations (Alderson and Beckfield 2004). These networks tie cities to one another and allow for different measurements of position or centrality in the network (Beckfield and Alderson 2006).

In-degree centrality is a simple measure of the number of connections coming into a city, normalized by the total number of possible connections in the network. This measure can only be obtained in a directed network, meaning the direction of the flows are known. For example, the information flowing from a firm's headquarters in Mumbai to its London branch is reflective of a directed network. Alderson and Beckfield (2004) equate this measure with prestige in the network, identifying cities where all the firms want to be. In-degree supports the idea of increasing economic returns, in that once a city has recognition as an industrial center, all firms that work in that area need to have a branch location there (Krugman 1990). In network theory, this phenomenon is referred to as Preferential Attachment and follows a power law distribution. Simulations of preferential attachment create highly stratified networks like the ones hypothesized by World Cities Theory (Easley and Kleinberg 2010; Friedmann 1986).

The opposite of in-degree centrality is out-degree centrality, in that the direction of the network link flows away from the city. Out-degree centrality is a representation of power because it represents the flow of information from source to destination. An alternative conception is that cities with more connections have more trading partners, and are not dependent on any individual city for economic exchange. This equates to power over those with few or no other connections who are highly dependent on a single relationship (Wasserman and Faust 2009).

The concept of dependence or independence is more accurately captured by the idea of closeness centrality. Cities with high levels of closeness centrality have more options in giving and receiving information. While this measure is related to in- and out-degree centrality, they should not be confused with one another, as this measure doesn't require a directed network. Both in- and out-links are treated equally.

Betweenness centrality is another nondirected measure and can be thought of as brokerage, or the cities that are access points to other parts of the network. Examples include regional hubs that allow hinterland areas access to broader markets. This measure is calculated by looking at the average number of links an individual city must travel through to reach all of the other cities in the network.

The final measure of centrality is different because it does not treat all links between cities as equal. Links to more central cities are given more weight. In other words, the number of links matters, but links to more central cities are weighted more heavily. This measure is referred to as Eigenvector centrality (Tranos 2011, 384).

As with the interlocking analysis, SNA revealed a highly unequal system of cities, with New York, London, Paris and Tokyo taking the top four positions in almost every measure (the exception being betweenness, with Dusseldorf taking New York's spot) (Alderson and Beckfield 2004, 830). Smith and Timberlake (2001) find roughly the same pattern at the top of the hierarchy, which remains stable over time. The stability of the top of world cities hierarchy has been shown in several analyses using both methods (Derudder et al. 2010; Orozco Pereira and Derudder 2010; Alderson, Beckfield, and Sprague-Jones 2010; Polese and Denis-Jacob 2010; Shin and Timberlake 2000). Those same studies, however, also show a fair bit of movement in the semiperipheral cities (Shin and Timberlake 2000; Mahutga et al. 2010; Alderson, Beckfield, and Sprague-Jones 2010). The most dramatic changes over the 20th century were Lagos and Casablanca as colonial empires selected these cities as primary economic hubs [Polese and Denis-Jacob (2010), p. 1849).

In terms of polarization, the SNA approach can look at similarities across several variables with a technique called block modeling, which was used by Alderson and Beckfield to organize cities into groups based on their position in the world city system (Alderson and Beckfield 2004, 824). This type of analysis is similar to the multinetwork typology used in the interlocking approach to separate out cities as coherent groups or classes (Wasserman and Faust 2009).

The problems with this method are that they cannot look at the strength of ties to regional headquarters, and therefore undervalue the regional headquarter cities (Taylor 2006). While these are drawbacks to the method, the strength of being able to eschew reliance on a preconceived set of industries and cities arguably outweighs those drawbacks (Taylor 2006). The linkage between network centrality and the Polarization Hypothesis depends on how each measure of centrality increases resource allocation to the APS workers. Connections are made in order to increase the capital of the firm making the link between cities. All connections are developed for the creation of capital but the different centrality measures should differ in the degree to which polarization increases. Out-degree should be indicative of greater returns to the APS workers because the links are being made for the express purpose of generating more capital and therefore generate more polarization. In-degree centrality is different because, while there is capital flowing in from other cities, there is an expectation of a return to the originator of the link. In-degree should still increase polarization but with less of an effect than out-degree.

The other three measures of centrality (eigenvector, betweenness and closeness) are nondirectional so capital retention, and the corresponding polarization, will be a mix of the high return out-degree, and lower return in-degree. The nondirectional measures are more representative of a general position in the world city network. Eigenvector ranks cities on the number of connections, betweenness on the importance of linking distinct subgroups, and closeness as the ease of movement through the network. Position in the network has been theoretically associated with dominance, but in diffuse nondirectional links it is unclear what advantage that dominance brings. Cities high in closeness centrality may have some connections to alpha global cities which in turn connect them with the vast majority of the network. At the same time the close cities may have a few ties to other small regional centers which extend their reach to areas untouched by the alpha cities. This does not necessarily confer any direct advantage to the close cities. The same statement could be made for cities high in betweenness centrality. If these nondirectional measures have an impact on polarization, and the actual position of a city in the network has an effect, then there will be a need for more theory to generate a causal link.

Using SNA based on the LexisNexis data I have constructed measures of in-degree, out-degree, betweenness, closeness, and eigenvector centrality for all of the cities for which I have data using the SNA package (Butts 2014). These centrality measures are used as independent variables in the statistical models described below. One of the problems with these data is that the LexisNexis database doesn't maintain historical snapshots, which means that the data on each firm only show the corporate hierarchy now, and not in the past. There have been a number of firms that no longer exist due to failure during the global recession of 2007-2010, or due to acquisition by other firms, which lowers the total number of firms. Tables 1 -2 display the top five cities in each measure of centrality for the years 2002, and 2011. Although the data are retrospective there is clear variation at the top between the beginning and end of the study period. Figure 1 shows the variation in eigenvector centrality over the study period.

Polarization and Geography

The data being used to for the geographic and polarization components are a U.S. Census product called the Longitudinal Employment and Household Dynamics (LEHD). These data contain information at the block level of Census geography from the year 2002 onward. The information is composed of counts of individuals who fall into a variety of categories, including income and industry groupings. This dataset is unique in that it contains information at the most granular level of geographic and temporal detail.

The use of Census Block geography allows for investigation of minute spatial scales. A Census block is roughly a city or neighborhood block. The areas themselves are defined by roads, railroads, or bodies of water (Census 1994a). These natural boundaries from edges to urban landscapes and are used to demarcate places as opposed to spaces (Lynch 2007). The use of blocks allows for investigations of naturally occurring aggregations such as neighborhoods, socio-economic or racial boundary lines, or metro areas to be drawn without having to rely on the somewhat arbitrary Census Block Groups, or Tract aggregations. All other Census geographies are based on aggregations of these block units.

With any measurement of space, it is vital to appropriately define the unit of analysis. Sassen's work has primarily focused on cities, as has the work from the GaWC group (Sassen 1991; Sassen 2001; Taylor and Walker 2001; Taylor 2004). This emphasis on cities is argued to have a greater focus on the power that drives the global economy and the resultant inequalities (Sassen 2001, 80). A regional approach captures a greater swath of economic activity and is a more natural unit for analysis since it captures a labor market (Friedmann 1986; Kloosterman and Lambregts 2001).

Multiscale analyses help to avoid one of the major problems in geography where results are found to be valid only at a specific unit of analysis and fail to speak to broader processes that should act on all geographic units equally (J. R. Hipp 2002). For this reason all measurements of polarization will be aggregated to three different geographic scales, the metropolitan area, the metropolitan region, and the mega region.

The metropolitan area is defined by the U.S. Census as “that of a core area containing a large population nucleus, together with adjacent communities that have a high degree of economic and social integration with that core" (Census 1994b). As discussed above, Sassen’s spatial unit of analysis in New York was Manhattan, only one small aspect of an integrated urban area. It is possible that the movement out of Manhattan by manufacturing and the middle class was those groups moving to another borough, or even to New Jersey, which would not have drastically altered social or economic activity. Since urban cores are ill-defined, the Census’s metropolitan area serves as a useful, standard proxy. Census blocks can be aggregated to fit within the metropolitan boundaries even if the metropolitan boundary extends beyond state or county lines.

An issue with the metropolitan areas is that over time they have sprawled into one another, creating larger urban agglomerations (Garreau 1991; Lang 2003). This trend can be accounted for by aggregated metropolitan areas whose boundaries are within five miles of each other into metropolitan regions. These agglomerations have become as economically integrated as metropolitan areas due to increases in transportation access and technology. A local example is the fact that the Wasatch Front is composed of three distinct metropolitan areas, Ogden–Clearfield, Provo-Orem, and Salt Lake City. While delineated as separate, independent entities, there is little to no clear demarcation as to where one ends and the next begins. There is deep integration between the three areas with commuters regularly living in one area and working in any of the others.

The concept of using commuting patterns to define a network of economic integration underlies the work of Guthrie (2007) and Nelson and Lang (2011) on defining mega regions. These areas have been seen since the late 1950s (Vicino, Hanlon, and Short 2007) and represent massive urban clusters that share labor markets and economic activity (Nelson and Lang 2011; Ross 2009). Florida has argued that mega regions constitute the natural economic unit of globalization (Florida, Gulden, and Mellander 2008, 459). This analysis aggregates census block data to Guthrie's (2007) boundaries of mega regions.

The LEHD is also the only Census dataset that contains high quality information for each year since 2002. While the decennial census contains the highest quality data and reaches the most people, it only occurs every ten years, missing the transformations within years. To fill the gap between the decennial census there is the American Community Survey (ACS), which is given to a statistically representative sample of the U.S. population every year. While it is statically representative, it only targets certain geographic areas, meaning that any particular urban area will only be surveyed every couple of years, leading to gaps in geographic coverage. The ACS provides three- and five-year rolling estimates for areas, but again, this leads to temporal gaps. The LEHD is the only dataset known to the author with the spatial and temporal resolution requisite for this study (A full discussion of the differences in the LEHD and other census products can be found in Appendix A).

The data are not without their own issues. The first issue is that it only contains information about employed individuals. The lack of unemployed individuals in polarization studies was brought up by (Burgers 1996) in a critique of Hamnett’s (1996) article on Dutch polarization. Another issue is the way income groups are broken out. In the LEHD, there are three fields that contain information comprising the income distribution: the count of individuals making less than or equal to $1,250 per month, those earning between $1,250-$3,333 per month and those earning more than $3,333 per month. This places all individuals who earn more than $40k per year into a single income group. While this does seem to skew the distribution far to the left, it is worth noting that much of the discussion about income inequality and distribution is based on household, not individual incomes. If a household had two income earners in the top LEHD bracket, they would be making at least $80k per year, just below the cutoff for Upper Middle Class according to Thompson and Hickey (2005). At the other end of the scale, the lowest income group makes less than $15k per year, which is below the threshold Thompson and Hickey give for the working class. With two income earners, the household itself would qualify as 'working class'. This framework is consistent with that of Warren and Warren (2003) which states that the only way the middle class has been able to remain stable since the 1970s has been to add more individuals into the labor market.

With this understanding, I will refer to those making less than $1,250 per month as low-income earners who, according to the Polarization Hypothesis, are expected to stay in the same geographic area. Those high-income earners (earning more than $3,333 per month) are also expected to stay in the urban areas. The definition of polarization itself will focus on the change of the middle income group, which is hypothesized to leave the urban areas as manufacturing jobs decline (Sassen 1991).

Another conception of polarization that will be used is defined as $(Inc_h + Inc_l) - ABS(Inc_h - Inc_l)$ which Timberlake (2012) developed as an effort to guard against mono-polarized income distributions. The high and low incomes are defined as the percentages of the population that are in the upper and lower quartiles of the income distribution. This measure will be referred to as Timberlake's Polarization.

Measures on spatial segregation and gentrification can be derived from the census blocks at each level of aggregation. For a measure of spatial segregation this analysis uses the percentage, and geographic area of blocks containing only individuals from a single income group that are not significantly different from their neighbors. The statistical significance will be determined by using a local Moran's I statistic, a measure of spatial randomness (Anselin 2010; Porter and Howell 2012). This statistic looks at a predefined number of neighbors (in this case eight) and determines its similarity to its neighbors. If an area is found to be significantly different from its neighbors, the area could be an area in transition from one state to another, or could be considered a boundary between different income clusters. The Moran's I statistic can also be aggregated up to a global measure of spatial randomness, but this requires the absence of clustering.

In gentrifying areas, one would expect to see a change in the composition of a block over time, from lower income to middle or higher income predominance. In the LEHD data, this phenomenon would manifest itself as either the proportion of low income earners decreasing or the proportion of middle income earners decreasing while the high income earners increased. This measure does not delve into the controversial aspects of gentrification, like the lower income earners being pushed out by rising rents (Freeman and Braconi 2004), but it does capture the expected geographic characteristics of change.

Table 1: Top 5 Cities by Network Centrality Scores for 2002

2002	eigenvector
Tokyo	1.00
London	0.94
New York, NY	0.69
Bangkok	0.64
Beijing	0.58

2002	closeness
Tokyo	8.5e-05
London	8.0e-05
New York, NY	7.9e-05
Paris	7.8e-05
Madrid	7.5e-05

2002	indegree
London	170
Tokyo	159
Madrid	124
New York, NY	118
Bangkok	107

2002	betweeness
Tokyo	297867
New York, NY	136599
London	114999
Paris	91261
Houston, TX	73065

2002	outdegree
Tokyo	2156
Paris	869
New York, NY	854
London	591
Munich	461

Table 2: Top 5 Cities by Network Centrality Scores for 2011

2011	**eigenvector**	**2011**	**closeness**
Tokyo	1.00	Tokyo	8.8e-05
London	0.87	London	8.1e-05
Beijing	0.69	New York, NY	8.0e-05
Shanghai	0.68	Paris	7.9e-05
Bangkok	0.63	Dublin	7.7e-05
2011	**indegree**	**2011**	**betweeness**
Tokyo	165	Tokyo	305792
London	165	New York, NY	149785
Shanghai	115	London	124624
New York, NY	114	Paris	97683
Madrid	111	Amsterdam	72745
2011	**outdegree**		
Tokyo	2168		
New York, NY	825		
Paris	775		
London	521		
Munich	461		

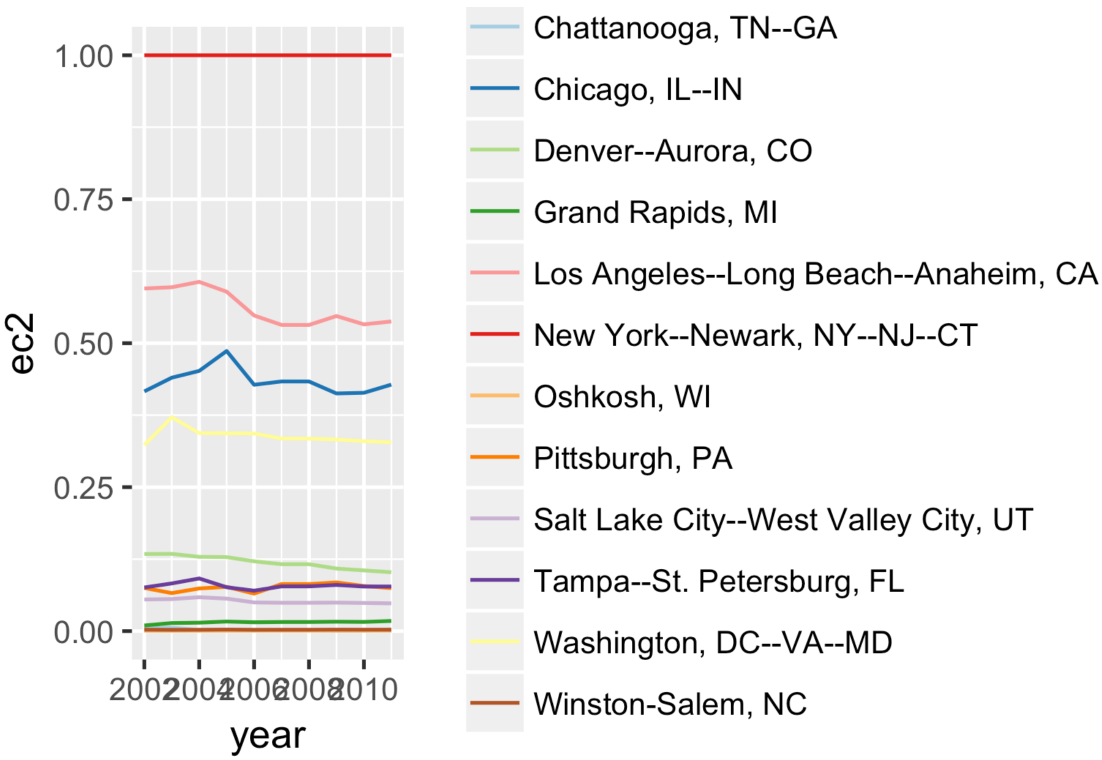

Figure 1: Eigenvector centrality for representative U.S. cities over the study period 2002-2011

Table 3: Summary Statistics

Statistic	N	Mean	St. Dev.	Min	Max
Total Employment	3,021	220,839.00	646,047.00	10,004	7,837,594
Low Income Earners	3,021	57,890.00	165,118.00	2,087	1,973,480
Middle Income Earners	3,021	80,494.00	224,765.00	2,899	2,619,483
High Income Earners	3,021	82,455.00	261,797.00	1,309	3,811,664
F.I.R.E. Employment	3,021	15,467.00	53,259.00	205	735,047
Manufacturing Employment	3,021	20,372.00	54,908.00	172	656,106
Management Employment	3,021	3,901.00	12,187.00	12	147,097
Eigenvector Centrality	3,021	0.03	0.09	0.00	1.00
In-Degree Centrality	3,021	15.00	41.00	0	432
Out-Degree Centrality	3,021	27.00	118.00	0	1,688
Betweenness Centrality	3,021	960.00	5,215.00	0.00	78,303.00
Closeness Centrality	3,021	0.0000	0.0000	0.00	0.0000
Timberlake Polarization	3,021	30.00	177.00	0.00	6,887.00
Percent of Middle Income Earners	3,021	0.39	0.06	0.22	0.59
Census Blocks	3,021	6,450.00	15,902.00	286	159,564
Gentrified Blocks	2,722	132.00	256.00	1	2,258

METHODS

Following Timberlake's (2012) quantitative approach to understanding of GCT and the Polarization Hypothesis, regression modeling will be used to test the first several hypotheses. Timberlake et al. used a linear regression model to determine the correlation of several variables in predicting polarization.

In Timberlake's analysis, the data used were unique in the polarization literature because they did not contain any temporal element. The data were a snapshot taken from the 2000 decennial census. In this analysis, time will be added back into the regression model, combining the strengths of Timberlake's statistical approach and the change over time found in the rest of the literature (Vaattovaara and Kortteinen 2003; Baum 1997; Hamnett 1996; Burgers 1996; Kempen 1994; Sassen 1991).

However, adding more time points calls for modifications to standard OLS regression models. One of the models used in this analysis will be a fixed-effects model. Fixed-effects models are useful for removing any unobserved, nonvarying heterogeneity within each urban area. Models will be run for several different dependent variables dealing with income polarization. The first dependent variable will be Timberlake's polarization, the second will be the percentage of middle income earners. For hypotheses 1-3, the independent variables will be the percentage of people employed in Manufacturing, and F.I.R.E. industries. To test hypotheses 4-5, the variables of network centrality will be added to the analysis. The variables of total land area and total employment will be included as control variables.

Hypotheses 6-8 deal with gentrification and changes to the spatial structure of urban areas. The dependent variables for these models will be the proportion of blocks that have displayed a decrease in the number of low or middle class earners with an increase in the number of high income earners. This will capture the gentrification but avoid areas that are being depopulated. The same sequence of independent and control variables will be used to look for correlations between gentrification and industry employment.

Hypothesis 9 is that the correlations between Manufacturing and F.I.R.E. jobs should be consistent at multiple geographic scales. The models mentioned above will be run at multiple geographic scales. Since the modification of scales requires a different dataset be used, an F-Test is not an available metric to compare the models. Instead, the standardized regression coefficients will be graphed for a visual analysis of parity. If the Polarization Hypothesis does not function the same way at different geographic scales, we should see large differences in the standardized coefficients between the different areas.

Nonlinear dynamical systems (NDS) models will be used to investigate the remaining hypotheses. These models have a different set of assumptions than OLS regression, which assume a linear relationship between the variables. Unfortunately, many social systems, including economic patterns and urban developments, do not follow clear linear relationships. NDS is a theory for describing and predicting processes of change, such as polarization and gentrification (Guastello and Gregson 2011, 3). Some of the concepts that are relevant to this analysis include attractors, oscillations, and catastrophes.

Attractors are an area of stability over time and can represent a qualitative state of being, or phase state. Within the Polarization Hypothesis, there is an assumed state of polarization characterized by a small or diminishing middle class relative to upper and lower/working classes. There is also a state of nonpolarization that is described by the opposite pattern. At any given point in time, one can determine the state of a given city. But because cities are composed of so many parts, there will always be some movement in the actual data point that defines the phase state. If there is stability in the system, the attractor is referred to as a fixed-point attractor and is shown in time-series data as movement toward an asymptotic bound (Guastello and Gregson 2011, 4). Repellers are another type of fixed-point from which there is always movement away, toward an attractor. These rejection points can indicate a boundary between different phase states.

In addition to fixed-point attractors, there are oscillating attractors, where the system moves from state to state in a specific pattern. If two systems are moving in independent, but related manners, they could be considered coupled. Movement within each system affects the other, such as with movement in centrality in the WCS hierarchy and polarization. Both fixed-point (or set-point) and oscillatory models utilize Time Delay Reconstruction (TDR), a technique based on Taken's Theorem that the movement of a single variable over time contains information on the topological shape of the data from a complex system (Guastello and Gregson 2011; Butner et al. 2015). One of the best examples of this type of analysis is the Lorenz attractor (Figure 2).

The Lorenz attractor is composed of three variables, or coordinates, on an x, y, and z axis. The relationship between the three variables is known and can be expressed in the following equations:

$$\frac{dX}{dt} = a * X + Y * tZ \qquad \text{(Equation 1)}$$

$$\frac{dY}{dt} = b * (Y - Z) \qquad \text{(Equation 2)}$$

$$\frac{dZ}{dt} = -X * Y + c * Y - Z \qquad \text{(Equation 3)}$$

While the equations are known, the ability to predict the combination of x, y, and z becomes exponentially more difficult as one looks further into the future. This difficulty is one of the indicators that this system is chaotic, even though its parameters and relationships are known. However, by using observations of one of the three variables over time, it is possible to construct a rough model of the entire system. Urban systems and the Polarization Hypothesis can be considered in the same way, a complex system with multiple interacting pieces including individuals, firms, governments and other organizations. All of these actors are integrated with each other in complex relationships, but by using TDR it is possible to focus on a single variable over time and through its movement develop a rough model of the complete structure.

Catastrophes are similar to repellers in that they describe a change from one state to another and are used specifically for looking at discontinuous change. The discontinuous change from nonpolarized to polarized state is theoretically possible due to centrality within the global economy. Given the distinct clusters of hierarchy in the WCS and the observation that those at the top of the hierarchy are the same cities that have been found to exhibit polarization and gentrification (Sassen 1991; Chiu and Lui 2004; Butler and Lees 2006), it can be expected that once a city reaches a certain level of centrality there would be a shift from nonpolarization to polarization. The same could be said of the percent of manufacturing jobs or F.I.R.E. jobs within an area. Each of these variables is tested below as a control variable in a catastrophe model.
To help explain the methods, the following charts have been prepared. In Figures 3-6, four plots are displayed with the same initial conditions or starting points. Over time, we can see how each scenario differs depending on the beta and alpha values interacting with the initial conditions. In these charts, we can see each of the topological constructs described above. In the scenarios represented by Figure 3 all values seem headed toward a single point, an attractor. In Figure 4, by changing the value to 0.5, two stable states are visible, depending on the initial conditions. Each of the undeviating lines is an attractor and the large empty space represents a repeller. By modifying the alpha value, or control parameter, in Figure 5, there is a single attractor, but it is

more complex than the previous attractors because it is oscillating between two points. Specifically, it is displaying damped oscillations since the amplitude of the oscillation decreases over time. Figure 6 also displays oscillations that are stable over time.

These topological features can be determined through modifying multilevel regression models to examine the change in the dependent variable over time. The canonical form of a cusp catastrophe model is

$$\frac{df(y)}{dy} = y^3 - by - a \qquad \text{(Equation 4)}$$

The derivative can be estimated by taking the difference between the leading and lagging value in a time series and dividing by two. Since this then destroys two time periods of observations, it is essential to have a time series long enough that the absence of two periods will still leave enough data to model. The cusp model can then be rewritten in regression form

$$\frac{dy}{dt} = \gamma_0 + \gamma_1 Y^3 + \gamma_2 * Y^2 + \gamma_3 Y + \omega_0 Y + \omega_1 + e \qquad \text{(Equation 5)}$$

where $\frac{dy}{dt}$ is the dependent variable, the γs are regression coefficients of Y, and ωs are the coefficients representing the control parameters. The notation of γ and ω is due to these being second level terms, regressing each individual city on itself over time and then plugging in those coefficients back into the general equation.

These models will be run in the R programming language using the nlme and lme4 (Pinheiro et al. 2016; Bates et al. 2015) libraries designed for multilevel modeling.

While relatively new, these models have been used by sociologists to study segregation (Spaiser et al. 2016) and discussed as being a type of study more closely aligned to the complex processes sociologists study (Castellani and Hafferty 2009), particularly urban phenomena in a global environment (Urry 2007).

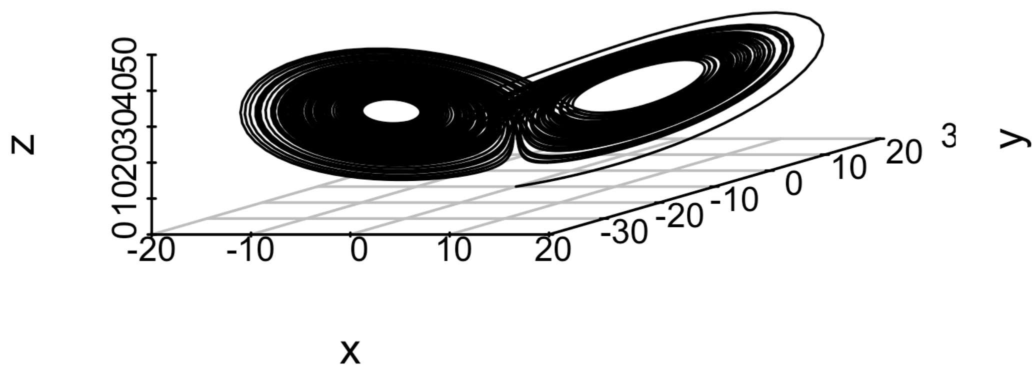

Figure 2: Lorenz Attractor

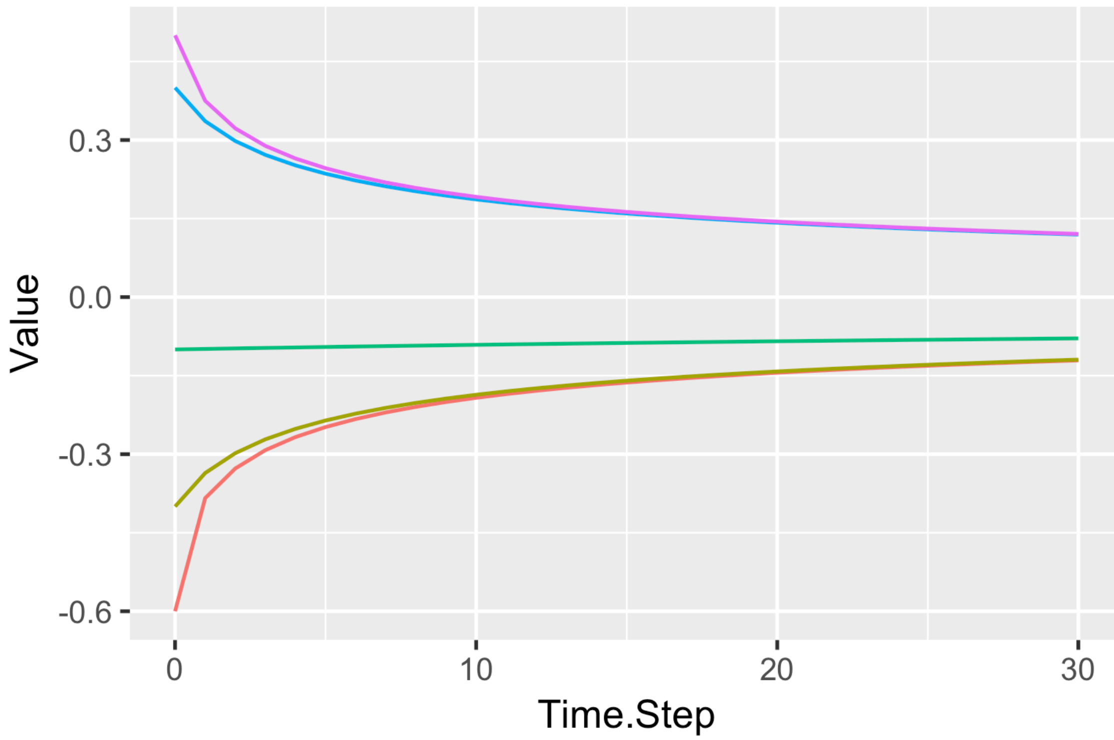

Figure 3: Change over Time - Beta = 0, Alpha = 0

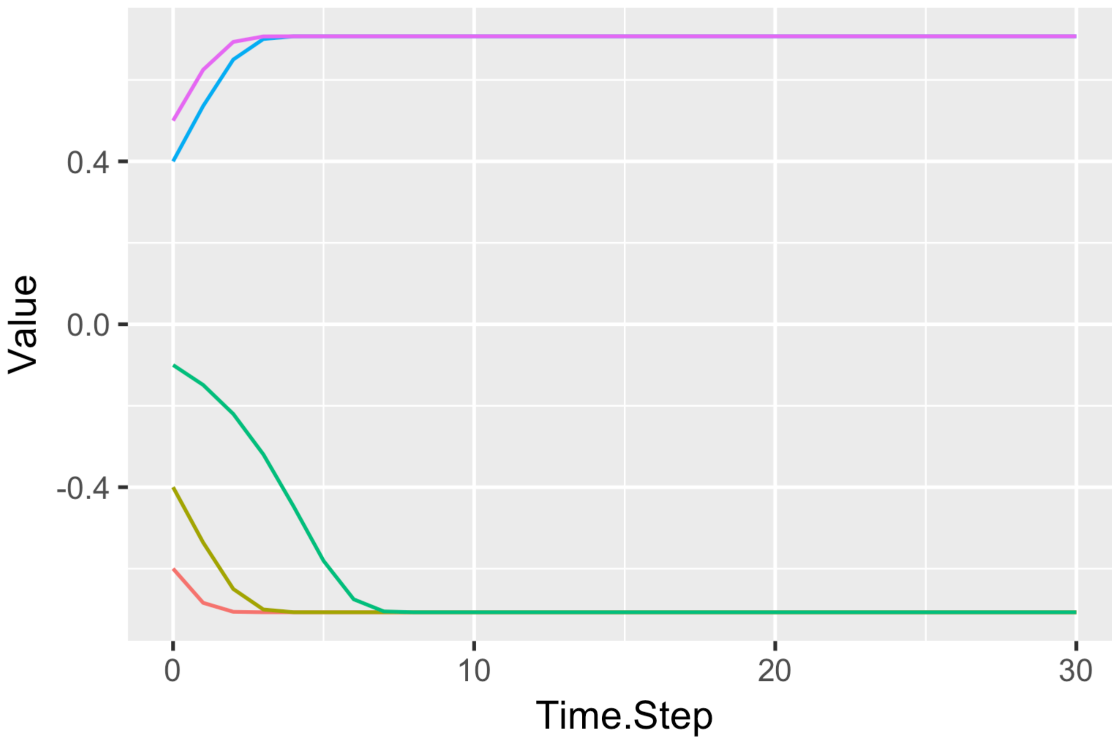

Figure 4: Change over Time - Beta = 0.5, Alpha = 0

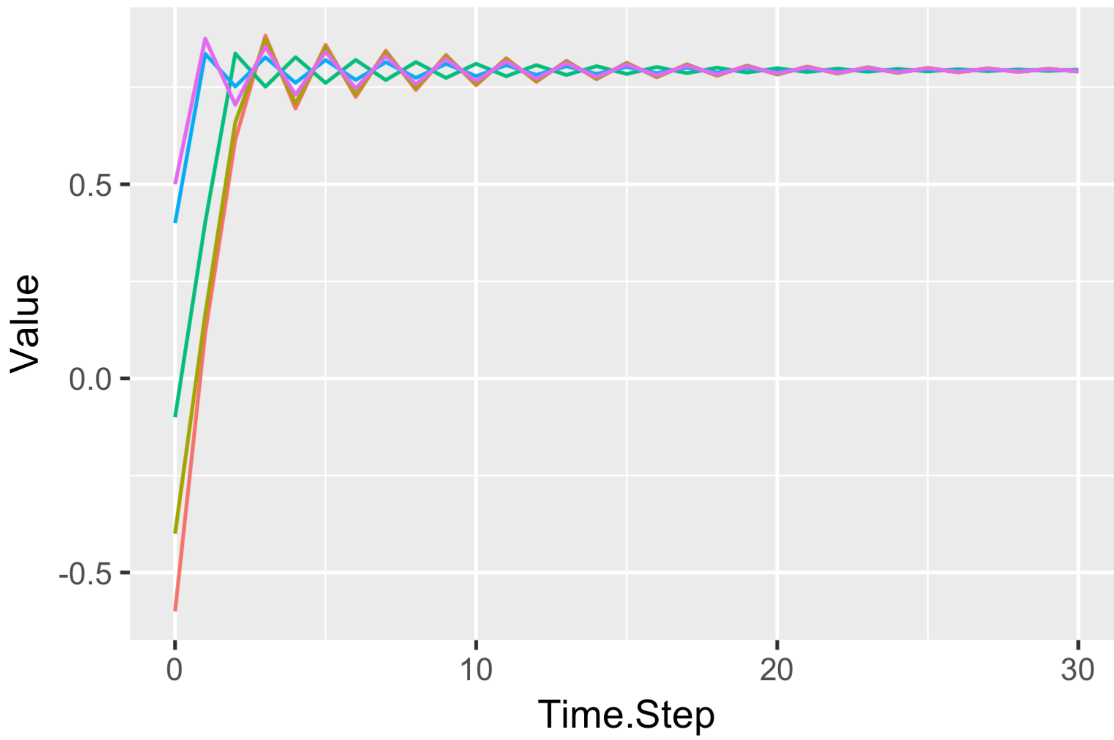

Figure 5: Change over Time - Beta = 0, Alpha = 0.5

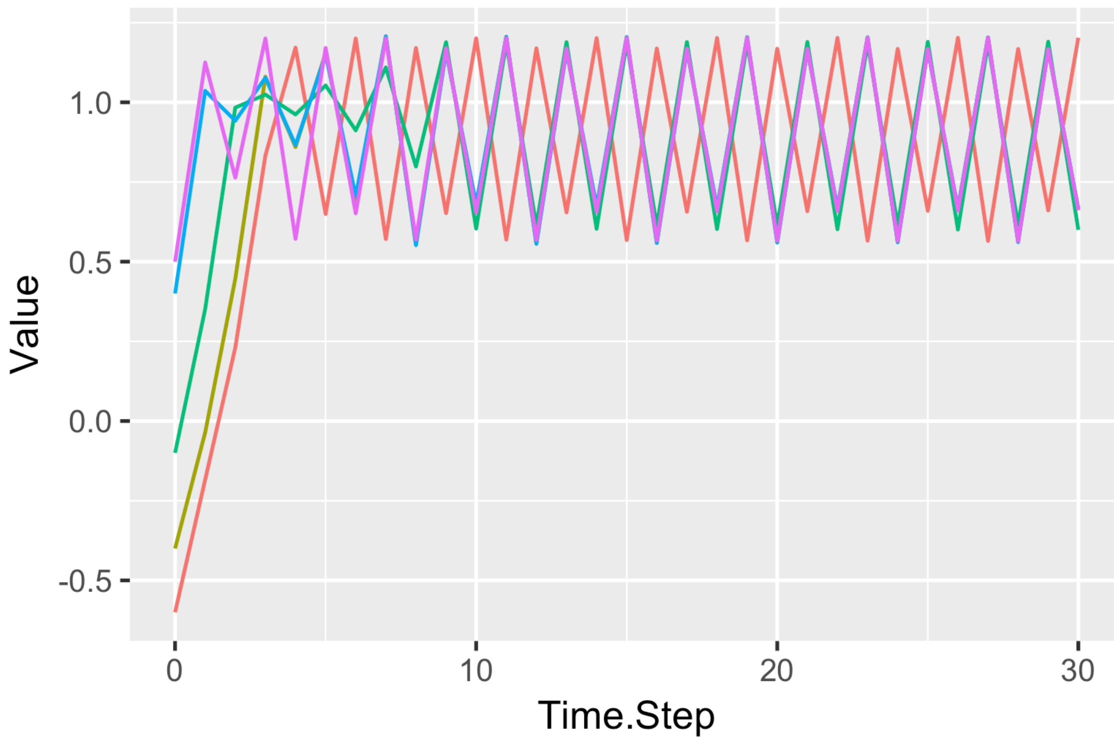

Figure 6: Change over Time - Beta = 0.5, Alpha = 0.5

RESULTS

The investigation of polarization is complicated due its multiple facets. Polarization has both an income distribution and spatial organization component. The income distribution can further be analyzed in terms of the relative balance at the upper and lower end of the distribution, or the changes to the size of the middle class. Spatial polarization can be viewed in terms of the number, size, and proportion of areas dominated by high, middle, or low income earners.

In this chapter each facet of polarization will be analyzed in its own section. The analysis will be composed of models designed to evaluate the correlation of each facet with 1) the economic structure, 2) position in the World System of Cities, and 3) changes to the geographic definition of the city.

Polarization’s Existence and Variation Through Time

There are two facets of income polarization, the size of the middle class, and the balance of the high and low income groups. Statistical models have been run with Timberlake's Polarization measure representing the balance between the high and low income groups, and the percentage of middle income earners representing the middle class.

Timberlake's Polarization: Balance in the Poles

Models 1-4 (Table 4) test the argument that APS and manufacturing firms are key factors needed to understanding polarization. The results indicate that there is no significant correlation between the economic structure and the balance between the high and low income groups (at the $p<0.05$ level). Though the results are not statistically significant the direction of the correlation coefficients is consistent with the Polarization Hypothesis. Both the percentage of F.I.R.E. and Management workers are associated with a decrease in Timberlake's measure indicating a lack of balance between the high and low income groups. The lack of balance is more indicative of general inequality as opposed to polarization.

Measures of centrality are added in models 5-10. Six measures of centrality are added to the models. The variable, connected, is a binary indication of a connection to the World System of Cities, and is a significant predictor of polarization. A city that is connected to the World system of Cities is correlated with a decrease in the balance of the poles of the income distribution.

The other centrality measures are not statistically significant and offer only marginal improvements to the overall model fit. The best fitting model uses closeness centrality as an independent variable, but has no variables that are significant. The lack of significance does not support the Polarization Hypothesis or Hypothesis 1.

The final test using Timberlake's measure is displayed in Table 5, which shows the standardized model results at both the metro area and the greater urban area (urban areas that have grown into one another). The major difference between the two geographic areas is that manufacturing employment is a stronger and more significant predictor of polarization in the greater urban area. To test hypothesis 7, that polarization processes are immune to issue of geographic scaling, Figure 7 plots the standardized coefficients found in Table 5 by geographic area, illustrating the difference associated with geographic scale. If the coefficients were equal at multiple geographic scales it would indicate that polarization processes exist independent of geographic size. However, there are a number of differences indicating the geographic scale is an important factor in understanding polarization.

When the percentage of middle income earners is the dependent variable all variables are statistically significant and in the direction indicated by the Polarization Hypothesis (Table 6). A one point increase in the percentage of manufacturing employment is associated with a .12 percentage point increase in the size of the middle income earners. This finding is directly in line with the Polarization Hypothesis linking manufacturing industries with middle class growth.

The correlation of the F.I. R.E. and Management variables is also in the direction indicated by the Polarization Hypothesis, but at much higher levels than that of Manufacturing. A one percentage point increase in F.I.R.E. and Management corresponds to approximately a one percentage point decrease in the middle class (0.98 and 1.3 percentage point correlations, respectively). The difference in the size of the correlations between Manufacturing and APS industries is an unexpected finding in light of the Polarization Hypothesis which discusses APS and manufacturing jobs as having equal weight of influence on the middle class.

The addition of centrality measures to the models increases the overall model fit to the data, with the best fitting model containing closeness centrality (AIC -9,901). Closeness centrality is the only measure of centrality that is not highly correlated with the total number of connections, and represents a flexible position within the network, due to the relative ease of reaching any other city in the network and is the best measure to indicate general network position (Timberlake et al. 2012). Increase in closeness centrality are associated with large decreases in the percent of middle income earners. The only other significant addition to the model is the binary variable indicating whether or not the city is connected to the Global City Network, which is correlated with a 0.02 percentage point decrease of middle income earners. As with Timberlake's measure, when models of middle income percentage were run at different geographic scales the results are different, indicating that polarization is not immune to factors of geographic scale.

Variables dealing with the economic structure are similar between the metro and greater urban areas, with increases in F.I.R.E. and Management employment associated with a decrease in the percentage of middle income earners (Figure 8). Manufacturing is also correlated with increased middle income earners at both geographic scales. The main difference between the two geographic scales is in the relationship between the middle class and position in the World Cities Network. In the Urban Regions, being connected is not statistically significant, unlike the Metro areas. Also, the centrality measures of in-degree, out-degree, betweenness, and eigenvector are all significantly correlated with decreases in the percentage of middle income earners in Urban Regions. These significant centrality measures are all highly correlated with one another. The combination of the centrality measures becoming significant and the connected variable not being statistically significant can be interpreted to mean that as Metro areas grow into larger agglomerations there are fewer areas that are not connected to the global economy.

Income Polarization Summary

In summary there is little evidence presented that income polarization exists in United States cities. There is growing inequality, as shown by the decreasing middle class (represented by the percentage of middle income earners), but there is no indication that the high and low income groups are of equal size, which is a requirement for polarization (Figures 9 - 10).

The findings are inconsistent at multiple geographic scales in opposition to hypothesis 7 (The model fit of polarization shouldn't change at different spatial scales). The other hypotheses (H1: Polarization exists, and it can be seen growing over time; H2: Polarization has a positive correlation with F.I.R.E. employment; H3: Polarization has a negative correlation with Manufacturing Employment) have mixed support depending on the dependent variable being used. Being connected to the network and Closeness centrality are the network variables that are correlated with income polarization.

The decline of the middle class shows a strong correlation to the factors described in the Polarization Hypothesis. The correlations between the APS employment variables are both significant and in the direction expected by the theory, supporting hypotheses 1-3. These findings do lend support for the Polarization Hypothesis if Polarization is narrowly defined as changes to the middle class.

Spatial Polarization and Gentrification

This second set of analyses focuses on spatial segregation and gentrification. The spatial aspects of the Polarization Hypothesis are often overlooked, though they share similar theoretical causes of APS firms and employees paying more for premium real estate and pricing out less profitable entities (Abrahamson 2004). Like income polarization there are several ways to look at spatial polarization. Dependent model variables include the percentage of city blocks that are overwhelmingly populated by low, middle, and high income earners and gentrification. The model structure follows the pattern of previous analysis by focusing on the economic structure, then centrality before investigating the difference in geographic scales.

Low Income Blocks

Low income blocks are city blocks that are 100% populated with low income earners and are surrounded by blocks that are also filled with low income earners. The results of the models (Table 8) show the correlation of the percentage of low income blocks with the economic and centrality measures. All variables, with the exception of betweenness centrality, are significant predictors of the percentage of low income areas.

All coefficients are also negative, indicating that that increases in F.I.R.E, Management, or Manufacturing jobs decreases the percentage of low income blocks in metro areas. The only major difference between the APS jobs (F.I.R.E. and Management) and Manufacturing is the scale. A one percent increase in APS employment corresponds to a .15 percentage point decrease in low income blocks, while a similar increase in Manufacturing is associated with a .06 decrease in low income blocks.

The coefficients for the centrality measures, except for closeness, are minuscule. The addition information provided by the centrality measures do not appear to increase the overall model fit as evidenced by the larger AIC values for models 6-10. This lower AIC value, combined with the low coefficient values, suggest there is little connection between the percentage of low income blocks and connection with the network of world cities.

Similar models were run comparing the Metro areas with the Urban Regions, with similar results (Table 9). The primary differences are that the percentage of management employment, out-degree, closeness and betweenness centrality is not significant. Figure 11 shows the difference in the standardized coefficients between the two geographic units. Unlike the income polarization measures there is little difference between the Metro Areas and Urban Regions when analyzing the percentage of low income blocks. The largest differences are with the betweenness and closeness measures of centrality, and the effect size of manufacturing employment. The percentage of manufacturing employment is the only variable that is statistically significant in all models, which also changed between the two spatial scales.

To summarize, the percentage of blocks dominated by low income earners are negatively correlated with growth in any of the APS or manufacturing jobs. This finding is consistent at both geographic scales, though, at the Urban Region level the relative strength of manufacturing employment is not as strong as in the metro area. The position of the areas in the World System of Cities does not display any noticeable correlation with the percentage of low income blocks.

The lack of correlation indicates that different processes are working to generate the spatial aspects of polarization than income distribution polarization. This finding is not unexpected because a city's centrality is theorized to only have a direct impact on the economic structure of the city, and therefore, only an indirect effect on the polarization.

Middle Income Clusters

According to the Polarization Hypothesis the percentage of middle income blocks should display similar correlations to the percentage of middle income earners discussed in the previous section. The model results in Table 10 show that, unlike the percentage of middle income earners, increases in Manufacturing employment is correlated with a decrease in the percentage of middle income blocks. The size of the correlations for increases in F.I.R.E. and Management employment are four times the size of the decreases associated with Manufacturing indicating that the potential impact of APS firms on changing the spatial landscape is much greater than the Manufacturing industry. A one percentage point increase in F.I.R.E. employment is associated with a quarter of a percentage point drop in the percentage of middle income blocks.

The only network covariates that are statistically significant are the binary variable connected and closeness centrality. The best fitting model is model 9 in Table 10 with an AIC of -12,068. In the Urban Regions, Eigenvector and In-Degree centrality are the position variables that are significant, though without a noticeable effect size (Table 11). Similar to the low income blocks, there is not much difference between the two geographic areas (Figure 12).

In brief there is mixed support for the Polarization Hypothesis. The direction of correlation with manufacturing employment is in a direction opposite of what is expected. The APS employment variables fall directly in-line with the Polarization Hypothesis. There does not appear to be much difference in scale indicating similar processes are likely at work in regard to employment. The difference in the centrality models between the two geographic regions suggests that at smaller areas being connected, and the diversity of those connections is of primary importance. At the larger geographic area the total number and type of connections have a greater association.

High Income Clusters

The model results for the high income blocks show a different pattern than the low and middle income blocks. The proportion of APS employment is not significant in the majority of the models, and the F.I.R.E. variable switches direction depending on the covariates indicating an unstable correlation with the percentage of high income blocks (Table 12). Manufacturing is significantly correlated with the dependent variable in all of the models, with a one percentage point increase in manufacturing employment corresponding to a .07 decrease in the percentage of high income blocks.

All of the network centrality variables are significant, with the best fitting model containing the closeness centrality measurement (Table 12 Model 9, AIC =-14,691). Table 13 shows the model results for the Metro and Urban Regions. There are several variables that are statistically significant at one scale, but not the other. The APS variables (F.I.R.E. and Management) are significant predictors at the Urban Region, but not the Metro area. The centrality measures are highly significant in the Metro areas, but not the Urban Regions (with the exception of closeness which is significant in all models.).

Figure 13 shows the difference in the standardized model coefficients between the two geographic areas. The relative impact of the all the variables of interest are much higher in the Metro areas than in the Urban Regions. The difference in the coefficients indicates that either different processes are at work in the two geographic areas or that the size of the area itself mitigates the correlation between the percentage of high income blocks and the independent variables.

In summary manufacturing employment and network centrality variables are significant predictors of the percentage of blocks dominated by high income earners. The correlation of these variables is much more pronounced in the small Metro areas. These findings provide mixed support for the Polarization Hypothesis, which expects a negative correlation between high income areas and manufacturing employment. However, there should have also been a positive correlation with the APS employment variables according to the theory. The difference in the centrality measures between the geographic areas supports the idea that polarization is attenuated by geographic scale (Fainstein 2000).

Gentrification

Gentrification is the change in an area from being dominated by low or middle income earners to middle or high income earners. The shift itself is what makes gentrification difficult to describe and measure. In this analysis gentrified blocks were identified as the proportion of blocks that have displayed a decrease in the percentage of low or middle class earners and an increase in the percentage of high income earners. This will capture the gentrification, but avoid areas that are being depopulated.

The model results show that all employment variables are significant predictors of gentrification in the negative direction (Table 14). The negative sign indicates that as employment percentages increase the percentage of gentrified blocks decreases. The variable associated with the largest decreases in gentrified blocks is the percentage of management employment (-0.16) as opposed to F.I.R.E. and Manufacturing (-0.06 and -0.04, respectively).

None of the centrality measures were found to be statistically significant. However being connected to the global network is a significant, though minute, predictor of gentrification.

The effect size of the all variables is more pronounced in the Urban Regions than the Metro areas (Table 15, Figure 14). The connected variable is not significant in the Urban Regions models, though it is significant in the Metro Areas. Regardless of scale the network centrality variables are not statistically significant. While the differences in effect size between the geographic scales are substantial, the only variable that is a significant predictor of gentrification in both models is the percentage of manufacturing employment. The Urban Regions are negatively correlated to a much higher degree with manufacturing than the Metro areas, indicating a very different set of processes occurring in the Urban Regions.

The results of the gentrification models indicate that employment of any kind decreases gentrification at both geographic scales. This finding is not expected in light of the Polarization Hypothesis, which theorizes that increases in APS employment should generate more gentrification, all other things being equal. The lack of significant correlation with centrality measures suggests that displacement of income groups is not a product of globalization, but a more localized phenomenon.

Spatial Polarization Summary

The models with spatial polarization as the dependent variables display a number of interesting patterns. First is that the blocks populated by the different income groups each show a unique group of statistically significant variables. Low and Middle income blocks are significantly correlated with all of the variables dealing with the economic structure as expected with the Polarization Hypothesis. However, the direction of the correlations is not expected. The greater presence of manufacturing employment should stand as a bulwark, protecting middle income earning areas from decline.

The evidence presented shows that increase in any of the employment sectors is correlated with a decrease in both low and middle income earning blocks as a percentage of all the blocks. The high income blocks are only significantly correlated with manufacturing employment. In other words, all employment variables are associated with a decline in the percentage of blocks dominated by a single income group. The decline can be caused by one of two things: either there are fewer blocks, or there is more mixing of income groups within a single block.

Figure 15 shows that during the study period there was a continual decline in the number of low and middle income dominated blocks and a corresponding increase in the number of high income blocks. The total number of blocks dominated by an income group remained fairly constant, but there was a marked increase in the number of high income blocks.

Gentrification increased over the study period (Figure 16), but the independent variables in the model only show negative correlations, indicating that the factors expected by the Polarization Hypothesis are not the primary drivers associated with increases in gentrification. Not only are the employment factors not descriptive of the increases in the high income blocks and gentrification, but the network centrality variables are not statistically significant in most models, leaving the models and the theory bereft of much explanatory power.

The initial hypotheses this analysis was designed to test were that gentrification should increase with F.I.R.E. or Centrality increases, and segregation (blocks dominated by single income groups) should increase with increase of F.I.R.E. jobs or centrality. Neither of the hypotheses has been confirmed with the models presented.

The related hypothesis that Polarization works irrespective of geographic scale is ambiguous. The model results show that (with the exception of low income areas) most of the model coefficients are different between the two units of geographic analysis, an indication that the processes do not work in the same manner and that geographic scale matters. On the other hand, the models do not appear to adequately describe spatial polarization processes, so the actual processes may be scale invariant.

Complexity in Polarization

Hypotheses 8 and 9 are based on the presence of multistability. The cusp catastrophe model assumes the possibility of multiple attractors, or stable states of polarization. To test the hypotheses cusp catastrophe models have been developed using F.I.R.E. employment percentages and measures of centrality as control parameters. The modeling strategy is composed of running four models for each combination of dependent variable and control parameters. Model one contains only the square and cube of the scaled and centered version of the dependent variables position at a given point in time. The second model will add in the position of the control parameter and the third model will add the velocity of change in the control parameter. The final model will add an interaction between the position of the dependent variable and the control parameter.

Income Polarization

Table 16 shows the results of the cusp model with change in Timberlake's polarization measure as the dependent variable, and closeness centrality as the control parameter. The model results indicate that the cusp model does not provide a great fit to the data. The model with closeness as a control parameter is the best fitting of all the models run with Timberlake's polarization measure as the dependent variable.

The cusp model (model 4) did not perform better than the baseline model based on AIC. This result is representative of all the cusp models run with income polarization as the dependent variable (both Timberlake's measure and percentage of middle income earners). The best fitting models for middle income earners used Out-Degree and Betweenness Centrality as the independent variable, with AIC values of -59 and -86, respectively. The cusp models did not perform better than the base models (tables for all the models referenced in this section are available in Appendix B).

Figure 17 shows the expected change in Timberlake's polarization over the next 50 years if current trends continue. This simulation is generated using the coefficients listed in Table 16. In complexity theory the initial conditions are key to projecting the future. Different starting values can generate wildly different results. In this case the starting values for the representative cities do not appear to make much difference to the end state of increased disparity in the poles shown by the decrease in Timberlake's polarization over time. To provide more context Figure 18 and 19 display the change in each of the selected cities over the course of the study period.

Complexity theory also allows for the investigation of the potential hidden patterns in the movement of variables over time. Figure 20 displays a vector flow field which shows the direction (arrow direction) and speed (arrow length) of expected movement over time based on the scaled and centered Timberlake Polarization and Closeness centrality. Figure 20 indicates a general movement toward lower levels of Timberlake's polarization, particularly when closeness centrality is low. Figure 20 also indicates some rotational aspects indicative of complex attractors. The existence of complex attractors is further bolstered by the approximation of set points which contain complex numbers. The combination of set points and the visual interpretation of Figure 20 is that there is a coupling relationship between measures of income polarization and closeness centrality, which is nonlinear.

Vector flow fields can also be generated for individual cities, taking into account the cities unique historicity. Figures 21-23 show the vector flow fields for Washington D.C., Salt Lake City, and Grand Rapids to show the individual variation lost in the generalized model. In Washington D.C. it looks like there are several positions of closeness and Timberlake's polarization that are expected to generate rapid imbalances between the poles of the income distribution. There is also the possibility of rapid balancing of the poles under the assumption of low centrality.

Salt Lake City appears to have two primary patterns, both associated with a decrease in centrality. The first is a rapid decrease in Timberlake's Polarization and the other with no decrease in polarization. The majority of paths in Grand Rapids move toward greater imbalance between the poles (as measured by a decrease in Timberlake's polarization) regardless of changes in centrality. There are a few positions where a rapid increase in Timberlake's polarization could be expected.

In summary the addition of complexity theory adds new nuance to the story of polarization. The interactions between the theorized dependent variables are not consistent over different cities, or even in similar directions within a single city. The complexity of the city and the global economy generates nonlinear patterns that can be difficult to observe when using linear models. While the patterns of interaction can be quite complex the simulation of the most likely path into the future indicate a continuation of greater imbalance in the poles of the income distribution and a lower percentage of middle income workers.

Spatial Polarization

The cusp models for spatial polarization variables are similar to those of the income models, namely a lack of statistical significance and no noticeable bifurcation. The one exception is shown in Table 17 representing the interactions between the percentage of middle income blocks and closeness centrality. Table 17 shows that there is a significant correlation between the percentage of middle income blocks and closeness centrality. Figure 24 illustrates the results of a simulation based on the closeness model, which shows that for the selected cities there is a single stable attractor.

The generalized vector flow field shows a clear trend for decreasing percentages of middle income blocks regardless of changes to closeness centrality. Figures 25-27 show the vector flow fields for Washington D.C., Salt Lake City, and Grand Rapids illustrating the individual variation lost in the generalized model. In Washington D.C. it appears that increases in closeness centrality will likely rapidly increase the percentage of middle income blocks. In Salt Lake City there are no noticeable paths for increasing middle income blocks. Both increases and decreases in closeness centrality appear to have the result of decreasing middle income blocks. Grand Rapids has an equal likelihood of increase or decreasing the percentage of middle income blocks, but only increasing in closeness centrality.

Cusp Summary

In general the hypothesis of multistability finds no support from the cusp models that were run. All simulations indicate that there is a single stable direction toward which all U.S. cities are heading. That stable point is of a decreased middle class, increased imbalance in the poles, more gentrification and blocks dominated by the high income earners. None of the control parameters displayed a significant enough impact to break the trajectory of increasing polarization. The stable state is in the negative direction for almost all of the dependent variables, which is consistent with the trends in the data described earlier in this paper.

While there is no evidence of multistability, there are complex patterns that emerge in both general models and for individual cities. The complex patterns are displayed with graphics illustrating possibilities of coupling effects, and oscillations. The complexity is reinforced with the complex numbers in the set points generated from the cusp models. In all, the picture of income and spatial polarization is nuanced, but with a decidedly negative trend.

Polarization in Mega Regions

There are 14 unique mega regions in the U.S. (Figure 29) (Guthrie 2007; Nelson and Lang 2011), which are made up of counties surrounding large urban areas and integrated through the commuting patterns of workers. Due to the limited number of mega regions, this section will focus on descriptions of the mega regions and how they compare with the other types of urban agglomeration.

The mega regions have a lower average percentage of middle income earners than the other metro area types and no outliers (Figure 30). Mega regions display two distinct outliers when looking at Timberlake's polarization (Figure 31), and a higher difference in the population in the high and low income groups than either of the other area types. This is due to the greater area of mega regions that encompass more of the hinterland and rural areas than any other area type. These outlying areas often have lower wages than the denser urban areas, leading to a much wider gulf in terms of incomes and lower income population.

The percentage of APS employment in mega regions is higher than that of other area types, with a much smaller range of variation (Figure 32). The percentage of manufacturing employees is very similar to the other urban areas. Most of the metro and urban regions are subsumed in the mega regions. The primary difference in the areas is that the mega regions contain the additional hinterlands not considered urban by the U.S. Census. This classification means that the difference in the means between mega regions and other urban agglomerations is due primarily to the addition of rural areas. Figure 33 shows that the mean of the mega regions is slightly lower than that of the other areas. This result indicates that the addition of hinterland areas does not influence the overall makeup of the manufacturing industry in the mega region. However, there is a difference in this hinterland addition in the percentage of F.I.R.E. employment. Mega regions have a much higher mean of F.I.R.E. employment percentage than urban areas alone, which means that the hinterlands contain a substantial number of F.I.R.E. jobs. This is in opposition to the Polarization Hypothesis which says that APS jobs need to be concentrated in urban areas.

In all measures of centrality, the mega regions have significantly higher centrality scores that either of the other areas. This pattern is due to the aggregation of nodes into the mega regions and the associated increase in the number of links flowing both in and out of the areas.

The increased centrality and APS jobs found in mega regions supports the use of the mega region for globalization analysis because those areas are where most of the global elites work. The mega regions are also far more connected than metropolitan areas, both internally through commuting and an integrated economy as well as to the global economy through the increased number of connections. While the increase in scale aligns mega regions with the global economy there is still quite a bit of variation between the different mega regions.

The Inland Empire and Wasatch Front mega regions are the only areas to have an increase in the number of middle income earners over the study period; all other areas experienced a net loss of workers in the middle class from 2002-2011 (Figure 34). Each area did exhibit large declines in the percentage of middle income earners (Figure 35). The largest declines (of around -7.14%) were in the Chicago and North East areas, with Hippies just under -7%. The Chicago and North East areas also started at a lower percentage of middle income earners than most of the other regions, only NorCal had a lower percentage in 2002.

Table 18 displays the mega regions' change over time in polarization and economic makeup. All areas lost manufacturing jobs, and manufacturing as a percentage of the economic makeup decreased by 1-3 percentage points for each area as well. F.I.R.E. employment increased for half the regions, but F.I.R.E. employment percentage only increased in three areas, and at less than 0.001 percentage points.

Florida, Inland Empire and the Wasatch Front all show increases in the Timberlake Polarization measure, indicating a larger gap between the number of high and low income earners. For the Wasatch Front and Inland Empire (which also saw increase in the total number of middle income earners), this indicates that while the middle class grew, the growth was not a rising tide that affected all earners equally.

There is a strong to moderate correlation in the change of both polarization measures and F.I.R.E., Manufacturing, and Management employees (Figure 36). These correlations are evidence in support of the idea that the larger the economy, the greater the disparity between high and low income earners. There are no strong correlations between the number of middle income workers and any of the industry categories described by the Polarization Hypothesis.

There are no strong correlations between middle income earners, polarization and the measures of centrality (Figure 37). Eigenvector centrality is moderately correlated with both the total number of middle income earners and Timberlake's polarization measure. Almost all of the regions experienced fluctuations in network centrality over time (Figure 38-42). The NorEast area remained at the top of the World System of Cities (as measured by eigenvector centrality) for the entire study period. While other Global Cities like London and Tokyo have vied for the ultimate position in the World City Network, when the geographic level is changed to mega regions, there is no comparison to the U.S. North East with New York City, Boston, Washington D.C. and all of their surrounding areas.

The NorEast region is also in a class by itself in comparison to all other U.S. mega regions in all measures of centrality. In all measures except for eigenvector centrality, the NorEast mega region, and most other mega regions, declined. The exception to this downward trend is the Wasatch Front, which increased in Out-Degree and Betweenness centrality, and remained stable with In-Degree centrality, though the starting point for each of these measures was quite low in comparison to the other areas.

Chicago, the Rust Belt and Hippies all increased in Out-Degree centrality, meaning there are more parent companies in each of those areas in 2011 than there were in 2002. The change in betweenness centrality is mixed, with a slight majority of mega regions increasing their centrality score while the rest decreased. All regions experienced similar fluctuations in closeness centrality over the study period. While the variation looks extreme (Figure 29), the actual changes are extremely minute.

In all the differences in centrality between the regions follow a core, semiperiphery, periphery pattern with the older and more established NorEast region with New York and Washington D.C. at the top of all the charts in terms of centrality. Regions such as the Inland Empire and Auto Zone representing the semiperiphery and the Wasatch Front and Front Range at the bottom in the periphery.

Mega Region Summary

In brief, the urban aggregation to mega region concentrates APS employment and measures of global connectivity. The concentration of resources exists, even though there are larger rural areas captured in the mega region's boundaries. The combination of concentration in the Mega region supports the idea that mega regions are a natural unit for the measurement of globalization, and therefore the unit at which polarization should be studied.

There is a great deal of variation between the different mega regions, following the core-periphery pattern expected by Freidman, which also supports using mega regions as the unit of analysis for polarization. The only difficulty is that there are so few mega regions that it is impossible to get a generalizable sample from only one country.

Table 4: Model Coefficents with Timberlake's Polarization as the Dependent Variable

	Timberlake's Polarization									
	1	2	3	4	5	6	7	8	9	10
Intercept	37.00***	54.00***	40.00*	41.00*	45.00**	46.00**	47.00**	46.00**	45.00**	45.00**
	(7.40)	(12.00)	(16.00)	(16.00)	(17.00)	(17.00)	(17.00)	(17.00)	(17.00)	(17.00)
Employment Density	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
F.I.R.E.		-356.00	-267.00	-133.00	-20.00	-25.00	-33.00	-29.00	-24.00	-19.00
		(198.00)	(211.00)	(222.00)	(226.00)	(233.00)	(233.00)	(229.00)	(227.00)	(229.00)
Manufacturing			68.00	81.00	96.00	96.00	96.00	95.00	96.00	96.00
			(54.00)	(55.00)	(55.00)	(55.00)	(55.00)	(55.00)	(55.00)	(55.00)
Management				-794.00	-638.00	-638.00	-639.00	-639.00	-639.00	-637.00
				(419.00)	(423.00)	(423.00)	(423.00)	(423.00)	(423.00)	(423.00)
Connected					-21.00**	-21.00**	-21.00**	-21.00**	-29.00	-21.00**
					(8.00)	(8.00)	(8.00)	(8.00)	(31.00)	(8.00)
Eigenvector						4.00				
						(40.00)				
In-Degree							.02			
							(.09)			
Out-Degree								.01		
								(.03)		
Closeness									33,591,009.00	
									(123,245,555.00)	
Betweenness										-0.00
										(0.00)
Observations	3,021	3,021	3,021	3,021	3,021	3,021	3,021	3,021	3,021	3,021
Akaike Inf. Crit.	39,856.00	39,843.00	39,833.00	39,818.00	39,807.00	39,800.00	39,812.00	39,814.00	39,770.00	39,822.00

Notes: *P < .05 **P < .01 ***P < .001

Table 5: Standardized Model Coefficents with Timberlake's Polarization as the Dependent Variable for Mulitple Geographic Areas

	Timberlake's Polarization											
	1	2	3	4	5	6	7	8	9	10	11	12
Intercept	46.00***	46.00***	46.00***	46.00***	52.00*	46.00***	46.00**	45.00**	45.00**	45.00**	48.00*	45.00**
	(6.90)	(6.90)	(6.90)	(6.90)	(24.00)	(6.90)	(14.00)	(14.00)	(14.00)	(14.00)	(24.00)	(14.00)
Employment Density	-.53	-.63	-.80	-.62	-.47	-.50	3.60	3.80	3.80	3.60	3.60	3.60
	(3.30)	(3.50)	(3.50)	(3.30)	(3.30)	(3.40)	(5.80)	(5.80)	(5.80)	(5.80)	(5.80)	(5.80)
F.I.R.E.	-.33	-.42	-.55	-.49	-.39	-.31	1.20	1.70	1.70	1.60	1.10	2.00
	(3.70)	(3.80)	(3.80)	(3.80)	(3.70)	(3.80)	(6.50)	(6.60)	(6.60)	(6.60)	(6.60)	(6.70)
Manufacturing	6.20	6.20	6.10	6.10	6.10	6.20	12.00*	12.00*	12.00*	12.00*	12.00*	12.00*
	(3.50)	(3.50)	(3.50)	(3.50)	(3.50)	(3.50)	(6.10)	(6.10)	(6.10)	(6.10)	(6.10)	(6.10)
Management	-5.20	-5.20	-5.20	-5.20	-5.20	-5.20	-8.80	-8.70	-8.70	-8.80	-8.80	-9.10
	(3.50)	(3.50)	(3.50)	(3.50)	(3.50)	(3.50)	(6.00)	(6.00)	(6.00)	(6.00)	(6.00)	(6.00)
Connected	-21.00**	-21.00**	-21.00**	-21.00**	-29.00	-21.00**	-18.00	-17.00	-17.00	-18.00	-21.00	-17.00
	(8.00)	(8.00)	(8.00)	(8.00)	(31.00)	(8.00)	(15.00)	(15.00)	(15.00)	(15.00)	(28.00)	(15.00)
Eigenvector		.36						-2.80				
		(3.60)						(5.70)				
In-Degree			.90						-2.60			
			(3.60)						(5.80)			
Out-Degree				.85						-2.30		
				(3.30)						(5.70)		
Closeness					3.60						1.30	
					(13.00)						(11.00)	
Betweenness						-.11						-3.40
						(3.40)						(5.70)
Observations	3,021	3,021	ffffddd3,021	3,021	3,021	3,021	1,723	1,723	1,723	1,723	1,723	1,723
Akaike Inf. Crit.	39,815.00	39,813.00	39,813.00	39,813.00	39,810.00	39,813.00	23,601.00	23,597.00	23,597.00	23,597.00	23,596.00	23,597.00

Notes: *P < .05 **P < .01 ***P < .001

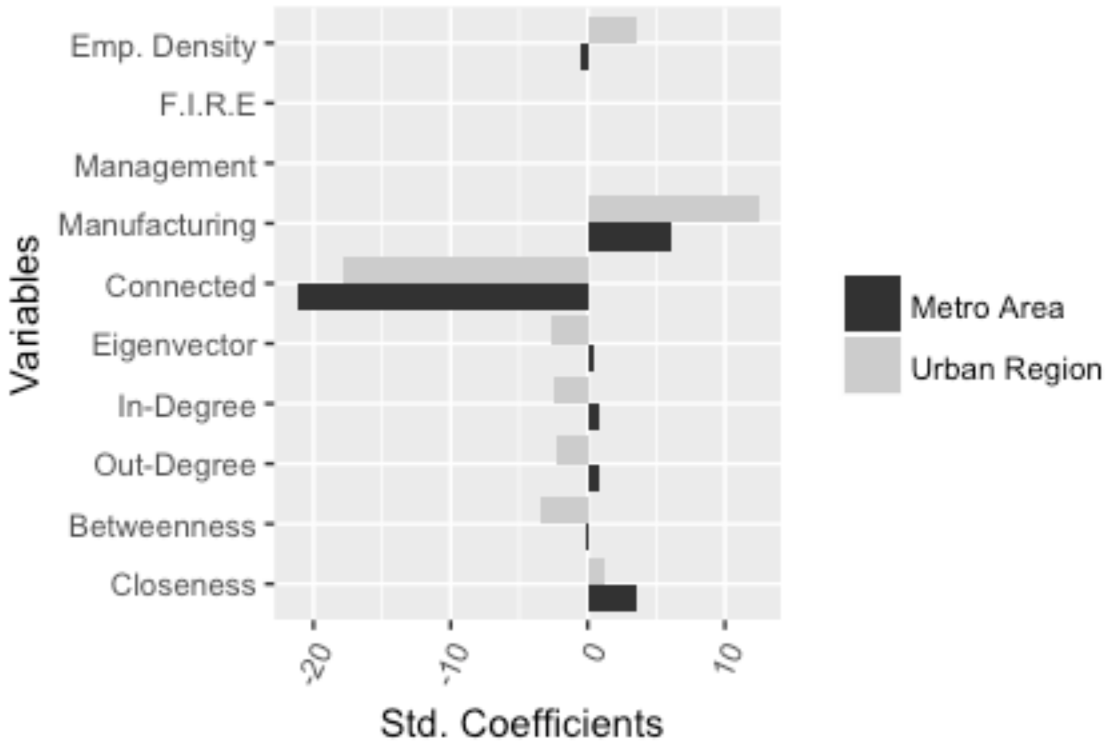

Figure 7: Standardized Fixed Effects Regression Coefficients – Timberlake's Polarization

Table 6: Model Coefficents with Middle Income Percentage as the Dependent Variable

	Middle Income Earners Polarization									
	1	2	3	4	5	6	7	8	9	10
Intercept	.41***	.48***	.46***	.46***	.46***	.46***	.46***	.46***	.46***	.46***
	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)
Employment Density	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
F.I.R.E.		-1.30***	-1.20***	-.98***	-.90***	-.91***	-.93***	-.91***	-.89***	-.89***
		(.05)	(.06)	(.06)	(.06)	(.06)	(.06)	(.06)	(.06)	(.06)
Manufacturing			.09***	.12***	.13***	.13***	.12***	.12***	.12***	.13***
			(.01)	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)
Management				-1.30***	-1.20***	-1.20***	-1.20***	-1.20***	-1.20***	-1.20***
				(.11)	(.11)	(.11)	(.11)	(.11)	(.11)	(.11)
Connected					-.01***	-.01***	-.01***	-.01***	.02**	-.01***
					(0.00)	(0.00)	(0.00)	(0.00)	(.01)	(0.00)
Eigenvector						0.00				
						(.01)				
In-Degree							0.00			
							(0.00)			
Out-Degree								0.00		
								(0.00)		
Closeness									-149,897.00***	
									(32,881.00)	
Betweenness										-0.00
										(0.00)
Observations	3,021	3,021	3,021	3,021	3,021	3,021	3,021	3,021	3,021	3,021
Akaike Inf. Crit.	-9,163.00	-9,718.00	-9,744.00	-9,881.00	-9,913.00	-9,904.00	-9,895.00	-9,890.00	-9,955.00	-9,883.00

Notes: *P < .05 **P < .01 ***P < .001

Table 7: Standardized Model Coefficents with Middle Income Earners as the Dependent Variable for Mulitple Geographic Areas

	Middle Income Earner Polarization											
	1	2	3	4	5	6	7	8	9	10	11	12
Intercept	.40***	.40***	.40***	.40***	.37***	.40***	.40***	.40***	.40***	.40***	.40***	.40***
	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)
Employment Density	-0.00***	-0.00***	-.01***	-0.00***	-.01***	-0.00***	-0.00***	-0.00**	-0.00**	-0.00***	-0.00***	-0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
F.I.R.E.	-.01***	-.01***	-.02***	-.01***	-.01***	-.01***	-.01***	-.01***	-.01***	-.01***	-.01***	-.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Manufacturing	.01***	.01***	.01***	.01***	.01***	.01***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Management	-.01***	-.01***	-.01***	-.01***	-.01***	-.01***	-.01***	-.01***	-.01***	-.01***	-.01***	-.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Connected	-.01***	-.01***	-.01***	-.01***	.02**	-.01***	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(.01)	(0.00)
Eigenvector		0.00						-.01***				
		(0.00)						(0.00)				
In-Degree			0.00						-.01***			
			(0.00)						(0.00)			
Out-Degree				0.00						-.01***		
				(0.00)						(0.00)		
Closeness					-.02***						-0.00	
					(0.00)						(0.00)	
Betweenness						-0.00						-0.00*
						(0.00)						(0.00)
Observations	3,021	3,021	3,021	3,021	3,021	3,021	1,723	1,723	1,723	1,723	1,723	1,723
Akaike Inf. Crit.	-9,905.00	-9,891.00	-9,893.00	-9,891.00	-9,914.00	-9,891.00	-6,223.00	-6,240.00	-6,237.00	-6,241.00	-6,211.00	-6,215.00
Notes:	*P < .05			**P < .01		***P < .001						

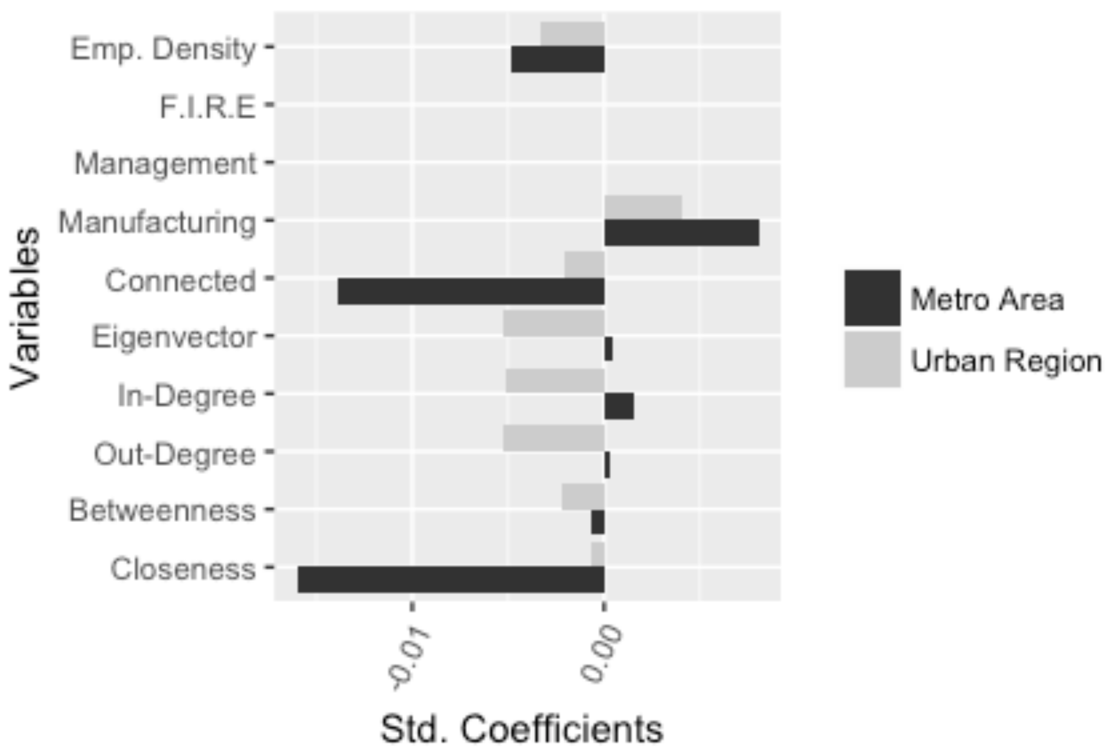

Figure 8: Standardized Fixed Effects Regression Coefficients - Middle Income Percentage

Table 8: Model Coefficents with High Income Blocks as the Dependent Variable

	High Income Earners Spatial Polarization									
	1	2	3	4	5	6	7	8	9	10
Intercept	.03***	.03***	.04***	.04***	.04***	.04***	.04***	.04***	.04***	.04***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Employment Density	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
F.I.R.E.		.05*	-.04	-.03	-.02	.01	.01	-.01	-.02	-.01
		(.02)	(.02)	(.02)	(.02)	(.02)	(.02)	(.02)	(.02)	(.02)
Manufacturing			-.07***	-.07***	-.07***	-.07***	-.07***	-.07***	-.07***	-.07***
			(.01)	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)
Management				-.04	-.03	-.03	-.03	-.03	-.02	-.03
				(.04)	(.04)	(.04)	(.04)	(.04)	(.04)	(.04)
Connected					-0.00**	-0.00*	-0.00*	-0.00**	.01**	-0.00**
					(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Eigenvector						-.02***				
						(0.00)				
In-Degree							-0.00***			
							(0.00)			
Out-Degree								-0.00**		
								(0.00)		
Closeness									-51,618.00***	
									(12,512.00)	
Betweenness										-0.00**
										(0.00)
Observations	2,758	2,758	2,758	2,758	2,758	2,758	2,758	2,758	2,758	2,758
Bayesian Inf. Crit.	-14,492.00	-14,484.00	-14,631.00	-14,620.00	-14,608.00	-14,623.00	-14,618.00	-14,583.00	-14,637.00	-14,576.00

Notes: *P < .05 **P < .01 ***P < .001

Table 9: Standardized Model Coefficents with High Income Blocks as the Dependent Variable for Mulitple Geographic Areas

	High Income Clusters: Spatial Polarization											
	1	2	3	4	5	6	7	8	9	10	11	12
Intercept	.03***	.03***	.03***	.03***	.02***	.03***	.03***	.03***	.03***	.03***	.02***	.03***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Employment Density	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
F.I.R.E.	-0.00	0.00	0.00	-0.00	-0.00	-0.00	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Manufacturing	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Management	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	0.00	0.00*	0.00*	0.00*	0.00*	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Connected	-0.00**	-0.00*	-0.00*	-0.00**	.01**	-0.00**	-0.00	-0.00	-0.00	-0.00	0.00*	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Eigenvector		-0.00***						-0.00				
		(0.00)						(0.00)				
In-Degree			-0.00***						-0.00			
			(0.00)						(0.00)			
Out-Degree				-0.00**						-0.00		
				(0.00)						(0.00)		
Closeness					-.01***						-0.00***	
					(0.00)						(0.00)	
Betweenness						-0.00**						-0.00
						(0.00)						(0.00)
Observations	2,758	2,758	2,758	2,758	2,758	2,758	1,650	1,650	1,650	1,650	1,650	1,650
Bayesian Inf. Crit.	-14,599.00	-14,610.00	-14,617.00	-14,584.00	-14,597.00	-14,584.00	-8,596.00	-8,578.00	-8,577.00	-8,576.00	-8,589.00	-8,575.00
Notes:	*P < .05		**P < .01		***P < .001							

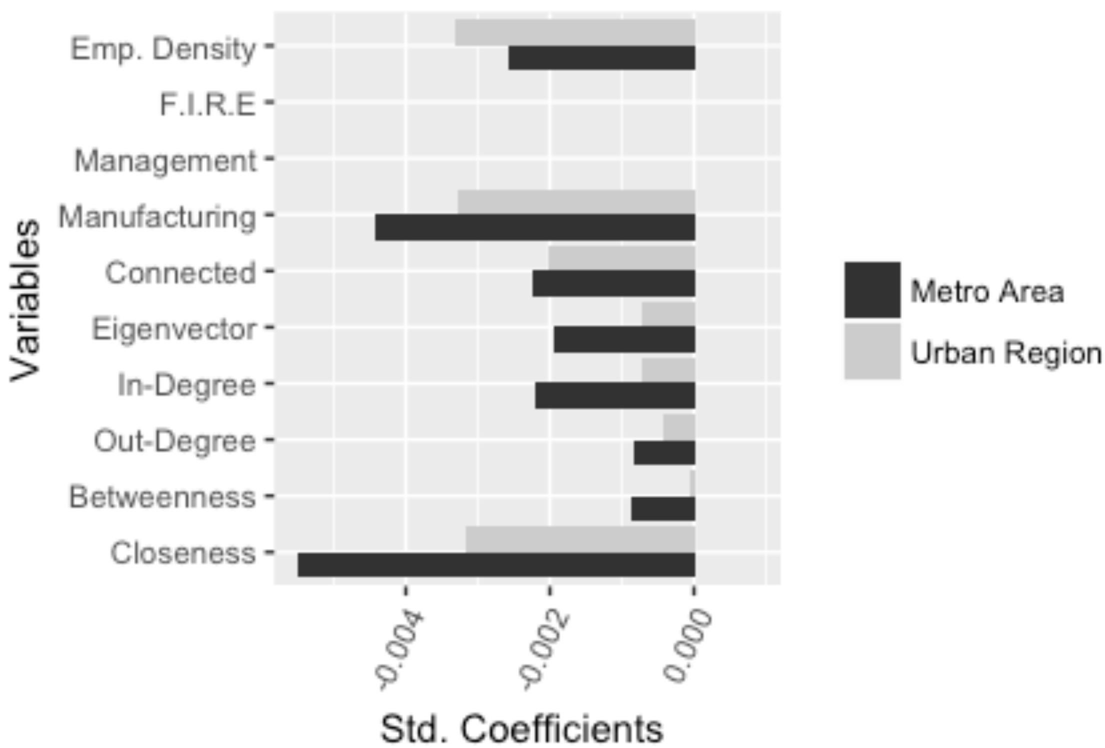

Figure 9: Standardized Fixed Effects Regression Coefficients High Income Blocks

Table 10: Model Coefficents with Low Income Blocks as the Dependent Variable

	Low Income Blocks: Spatial Polarization									
	1	2	3	4	5	6	7	8	9	10
Intercept	.03***	.04***	.05***	.05***	.05***	.05***	.05***	.05***	.05***	.05***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Employment Density	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
F.I.R.E.		-.09***	-.18***	-.15***	-.13***	-.11***	-.11***	-.12***	-.12***	-.12***
		(.02)	(.02)	(.02)	(.02)	(.02)	(.02)	(.02)	(.02)	(.02)
Manufacturing			-.07***	-.06***	-.06***	-.06***	-.06***	-.06***	-.06***	-.06***
			(.01)	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)
Management				-.14***	-.11**	-.11**	-.11**	-.11**	-.10**	-.11**
				(.04)	(.04)	(.04)	(.04)	(.04)	(.04)	(.04)
Connected					-0.00***	-0.00***	-0.00***	-0.00***	0.00	-0.00***
					(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Eigenvector						-.01**				
						(0.00)				
In-Degree							-0.00**			
							(0.00)			
Out-Degree								-0.00*		
								(0.00)		
Closeness									-34,530.00**	
									(12,134.00)	
Betweenness										-0.00
										(0.00)
Observations	2,756	2,756	2,756	2,756	2,756	2,756	2,756	2,756	2,756	2,756
Bayesian Inf. Crit.	-14,582.00	-14,591.00	-14,721.00	-14,720.00	-14,739.00	-14,730.00	-14,718.00	-14,711.00	-14,759.00	-14,703.00

Notes: *P < .05 **P < .01 ***P < .001

Table 11: Standardized Model Coefficents with Low Invome Blocks as the Dependent Variable for Mulitple Geographic Areas

	Low Income Clusters: Spatial Polarization											
	1	2	3	4	5	6	7	8	9	10	11	12
Intercept	.03***	.03***	.03***	.03***	.02***	.03***	.03***	.03***	.03***	.03***	.03***	.03***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Employment Density	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
F.I.R.E.	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Manufacturing	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Management	-0.00**	-0.00**	-0.00**	-0.00**	-0.00**	-0.00**	0.00	0.00	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Connected	-0.00***	-0.00***	-0.00***	-0.00***	0.00	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00	-0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Eigenvector		-0.00**						-0.00**				
		(0.00)						(0.00)				
In-Degree			-0.00**						-0.00**			
			(0.00)						(0.00)			
Out-Degree				-0.00*						-0.00		
				(0.00)						(0.00)		
Closeness					-0.00**						-0.00	
					(0.00)						(0.00)	
Betweenness						-0.00						0.00
						(0.00)						(0.00)
Observations	2,756	2,756	2,756	2,756	2,756	2,756	1,645	1,645	1,645	1,645	1,645	1,645
Bayesian Inf. Crit.	-14,730.00	-14,717.00	-14,717.00	-14,712.00	-14,719.00	-14,712.00	-9,048.00	-9,035.00	-9,034.00	-9,029.00	-9,028.00	-9,027.00

Notes: *P < .05 **P < .01 ***P < .001

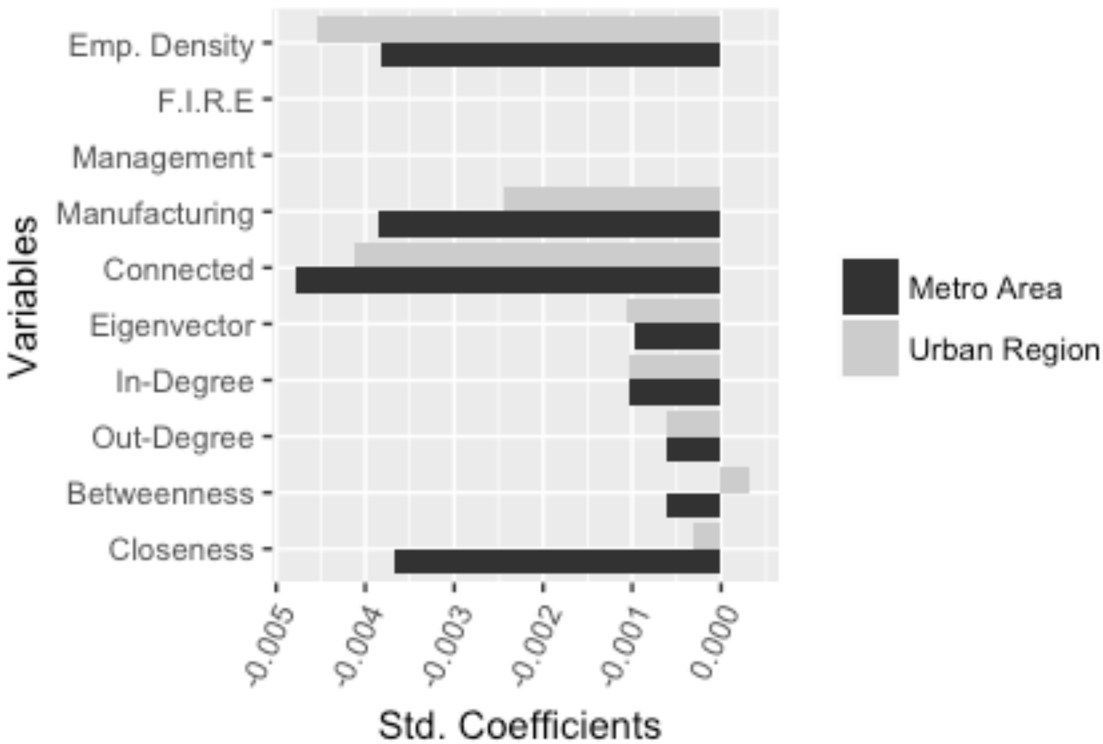

Figure 10: Standardized Fixed Effects Regression Coefficients Low Income Blocks

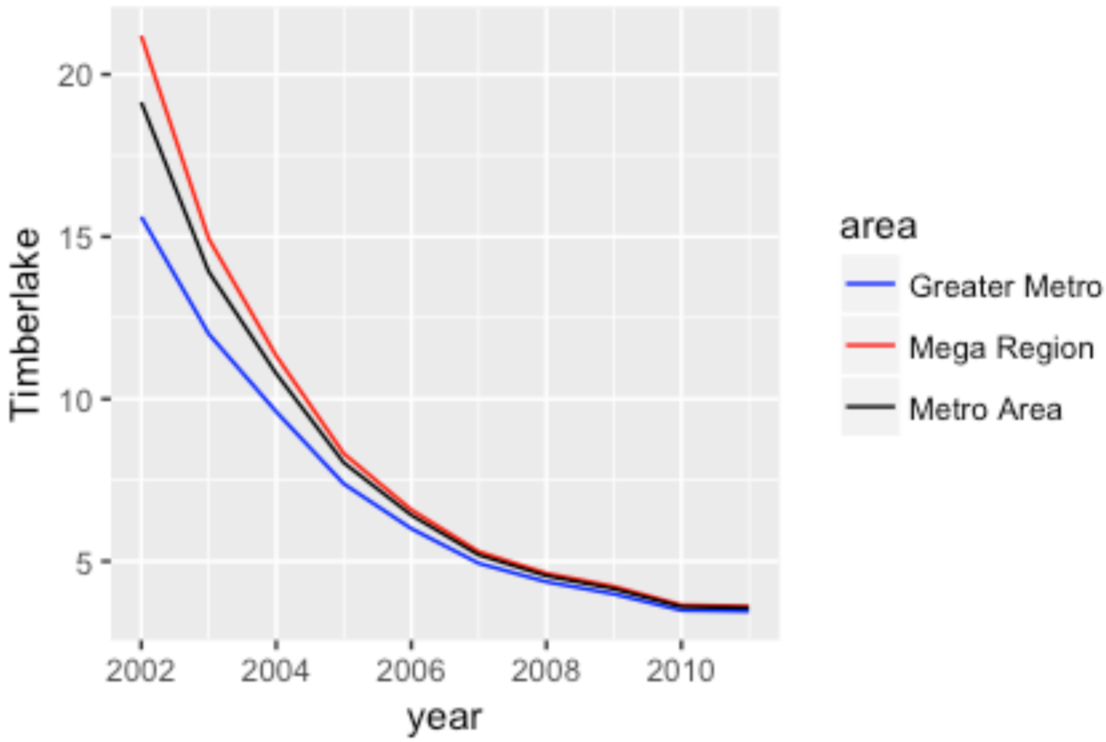

Figure 11: Timberlake Polarization over Time

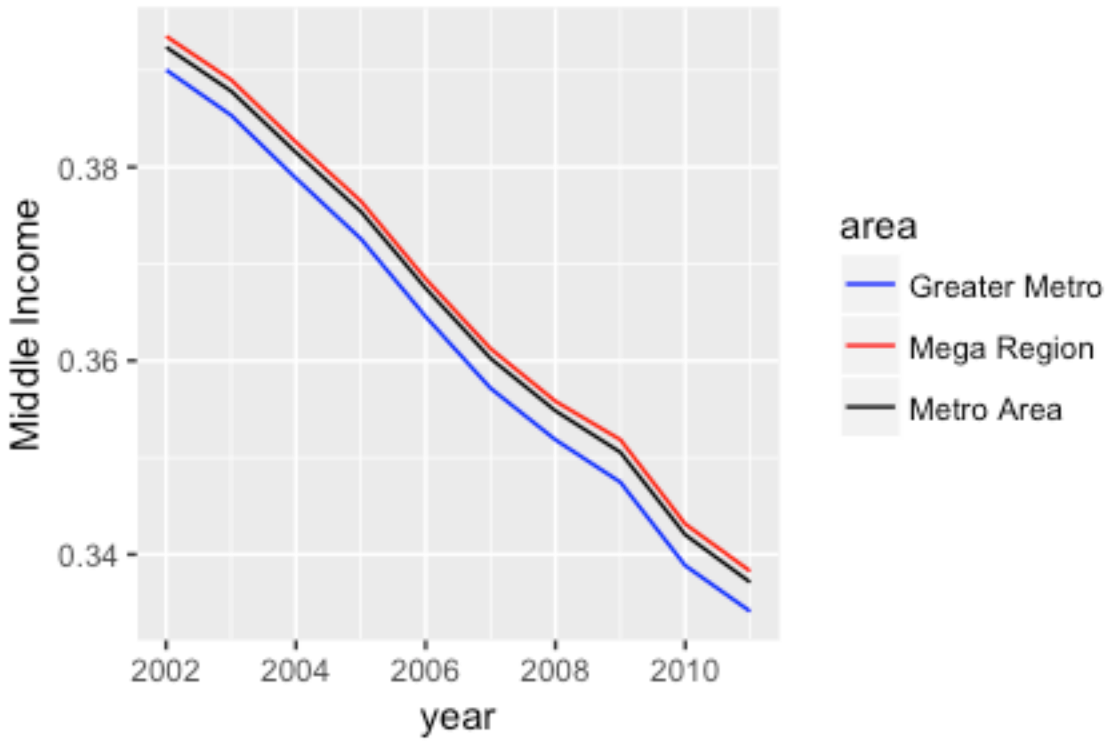

Figure 12: Middle Income Percentage Polarization over Time

Table 12: Model Coefficents with Middle Income Blocks as the Dependent Variable

	Middle Income Earners Spatial Polarization									
	1	2	3	4	5	6	7	8	9	10
Intercept	.06***	.07***	.08***	.08***	.08***	.08***	.08***	.08***	.08***	.08***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Employment Density	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
F.I.R.E.		-.22***	-.31***	-.25***	-.21***	-.19***	-.20***	-.21***	-.20***	-.21***
		(.03)	(.03)	(.04)	(.04)	(.04)	(.04)	(.04)	(.04)	(.04)
Manufacturing			-.08***	-.07***	-.06***	-.06***	-.06***	-.07***	-.07***	-.06***
			(.01)	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)
Management				-.36***	-.31***	-.31***	-.31***	-.31***	-.30***	-.31***
				(.07)	(.07)	(.07)	(.07)	(.07)	(.07)	(.07)
Connected					-.01***	-.01***	-.01***	-.01***	.01	-.01***
					(0.00)	(0.00)	(0.00)	(0.00)	(.01)	(0.00)
Eigenvector						-.01				
						(.01)				
In-Degree							-0.00			
							(0.00)			
Out-Degree								0.00		
								(0.00)		
Closeness									-70,945.00***	
									(20,036.00)	
Betweenness										-0.00
										(0.00)
Observations	2,759	2,759	2,759	2,759	2,759	2,759	2,759	2,759	2,759	2,759
Bayesian Inf. Crit.	-11,862.00	-11,895.00	-11,953.00	-11,970.00	-11,989.00	-11,975.00	-11,962.00	-11,958.00	-12,015.00	-11,951.00
Notes:	*P < .05		**P < .01		***P < .001					

Table 13: Standardized Model Coefficents with Middle Income Blocks as the Dependent Variable for Mulitple Geographic Areas

	Middle Income Clusters: Spatial Polarization											
	1	2	3	4	5	6	7	8	9	10	11	12
Intercept	.05***	.05***	.05***	.05***	.03***	.05***	.04***	.04***	.04***	.04***	.04***	.04***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Employment Density	-.01***	-.01***	-.01***	-.01***	-.01***	-.01***	-.01***	-.01***	-.01***	-.01***	-.01***	-.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
F.I.R.E.	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Manufacturing	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Management	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Connected	-.01***	-.01***	-.01***	-.01***	.01	-.01***	-0.00*	-0.00*	-0.00*	-0.00*	-0.00	-0.00*
	(0.00)	(0.00)	(0.00)	(0.00)	(.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Eigenvector		-0.00						-0.00**				
		(0.00)						(0.00)				
In-Degree			-0.00						-0.00*			
			(0.00)						(0.00)			
Out-Degree				0.00						-0.00		
				(0.00)						(0.00)		
Closeness					-.01***						-0.00	
					(0.00)						(0.00)	
Betweenness						-0.00						0.00
						(0.00)						(0.00)
Observations	2,759	2,759	2,759	2,759	2,759	2,759	1,653	1,653	1,653	1,653	1,653	1,653
Bayesian Inf. Crit.	-11,980.00	-11,962.00	-11,961.00	-11,959.00	-11,975.00	-11,959.00	-7,616.00	-7,603.00	-7,602.00	-7,599.00	-7,598.00	-7,597.00

Notes: *P < .05 **P < .01 ***P < .001

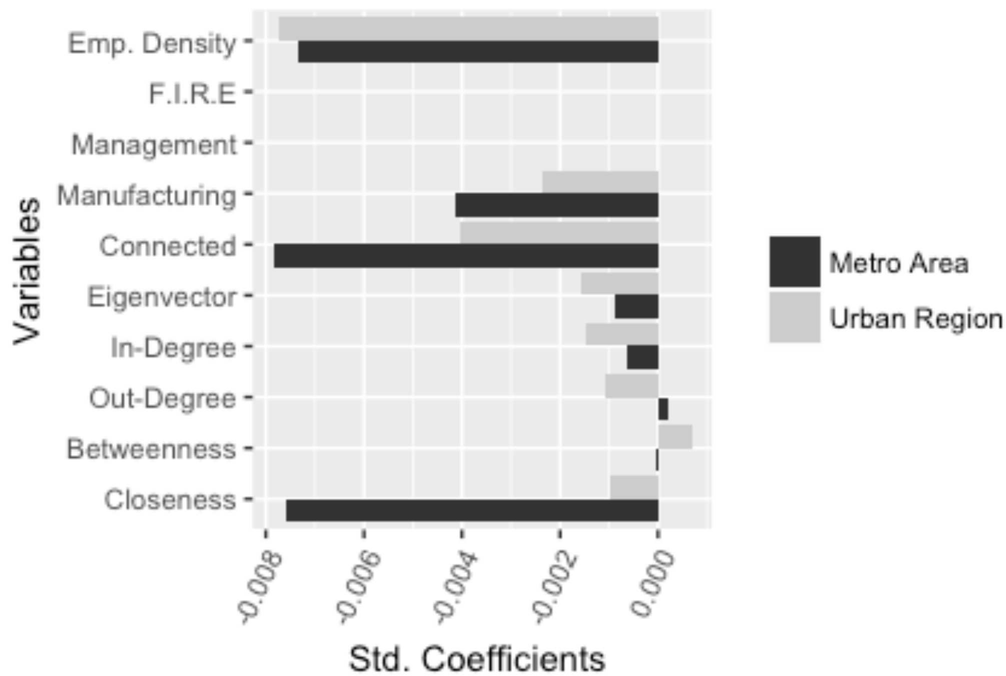

Figure 13: Standardized Fixed Effects Regression Coefficients Middle Income Blocks

Table 14: Model Coefficents with Gentrified Blocks as the Dependent Variable

	Gentrification									
	1	2	3	4	5	6	7	8	9	10
Intercept	.04***	.04***	.05***	.05***	.05***	.05***	.05***	.05***	.05***	.05***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Employment Density	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
F.I.R.E.		-.05***	-.11***	-.08***	-.06***	-.05***	-.05***	-.06***	-.06***	-.06***
		(.01)	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)
Manufacturing			-.05***	-.05***	-.04***	-.04***	-.04***	-.04***	-.04***	-.04***
			(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Management				-.18***	-.16***	-.16***	-.16***	-.16***	-.16***	-.16***
				(.03)	(.03)	(.03)	(.03)	(.03)	(.03)	(.03)
Connected					-0.00***	-0.00***	-0.00***	-0.00***	-0.00	-0.00***
					(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Eigenvector						-0.00				
						(0.00)				
In-Degree							-0.00			
							(0.00)			
Out-Degree								0.00		
								(0.00)		
Closeness									-10,321.00	
									(7,810.00)	
Betweenness										0.00
										(0.00)
Observations	2,489	2,489	2,489	2,489	2,489	2,489	2,489	2,489	2,489	2,489
Bayesian Inf. Crit.	-15,471.00	-15,472.00	-15,633.00	-15,667.00	-15,691.00	-15,675.00	-15,662.00	-15,660.00	-15,705.00	-15,652.00
Notes:	*P < .05		**P < .01		***P < .001					

Table 15: Standardized Model Coefficents with Gentrified Blocks as the Dependent Variable for Mulitple Geographic Areas

	Gentrification: Spatial Polarization											
	1	2	3	4	5	6	7	8	9	10	11	12
Intercept	.03***	.03***	.03***	.03***	.03***	.03***	.03*	.03*	.03*	.03*	.04	.03*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(.01)	(.01)	(.01)	(.01)	(.02)	(.01)
Employment Density	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	.02***	.02***	.02***	.02***	.02***	.02***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)
F.I.R.E.	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	.03***	.03***	.03***	.03***	.03***	.03***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)
Manufacturing	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-.02**	-.02**	-.02**	-.02**	-.01**	-.02**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)
Management	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-.02***	-.02***	-.02***	-.02***	-.02***	-.02***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)
Connected	-0.00***	-0.00***	-0.00***	-0.00***	-0.00	-0.00***	.02	.02	.02	.02	.02	.02
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(.01)	(.01)	(.01)	(.01)	(.03)	(.01)
Eigenvector		-0.00						-.01				
		(0.00)						(.01)				
In-Degree			-0.00						-0.00			
			(0.00)						(.01)			
Out-Degree				0.00						-.01		
				(0.00)						(0.00)		
Closeness					-0.00						0.00	
					(0.00)						(.01)	
Betweenness						0.00						-.01
						(0.00)						(.01)
Observations	2,489	2,489	2,489	2,489	2,489	2,489	1,488	1,488	1,488	1,488	1,488	1,488
Bayesian Inf. Crit.	-15,683.00	-15,661.00	-15,661.00	-15,661.00	-15,664.00	-15,661.00	-615.00	-600.00	-599.00	-601.00	-600.00	-600.00

Notes: *P < .05 **P < .01 ***P < .001

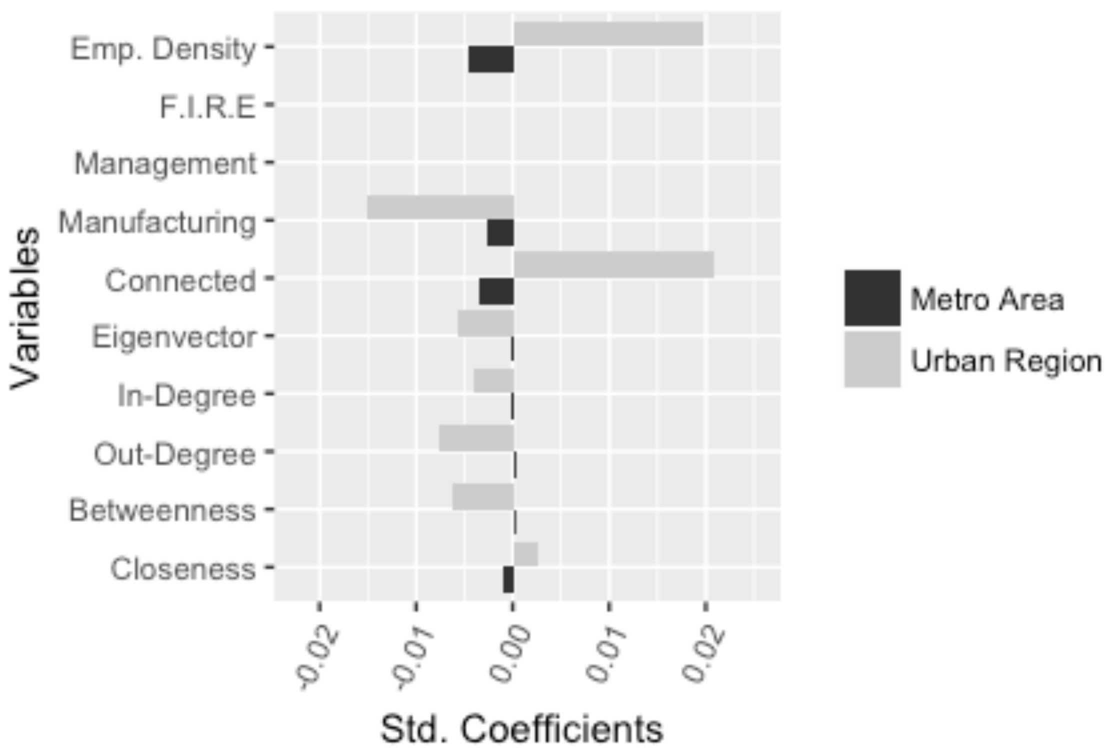

Figure 14: Standardized Fixed Effects Regression Coefficients Gentrified Income Blocks

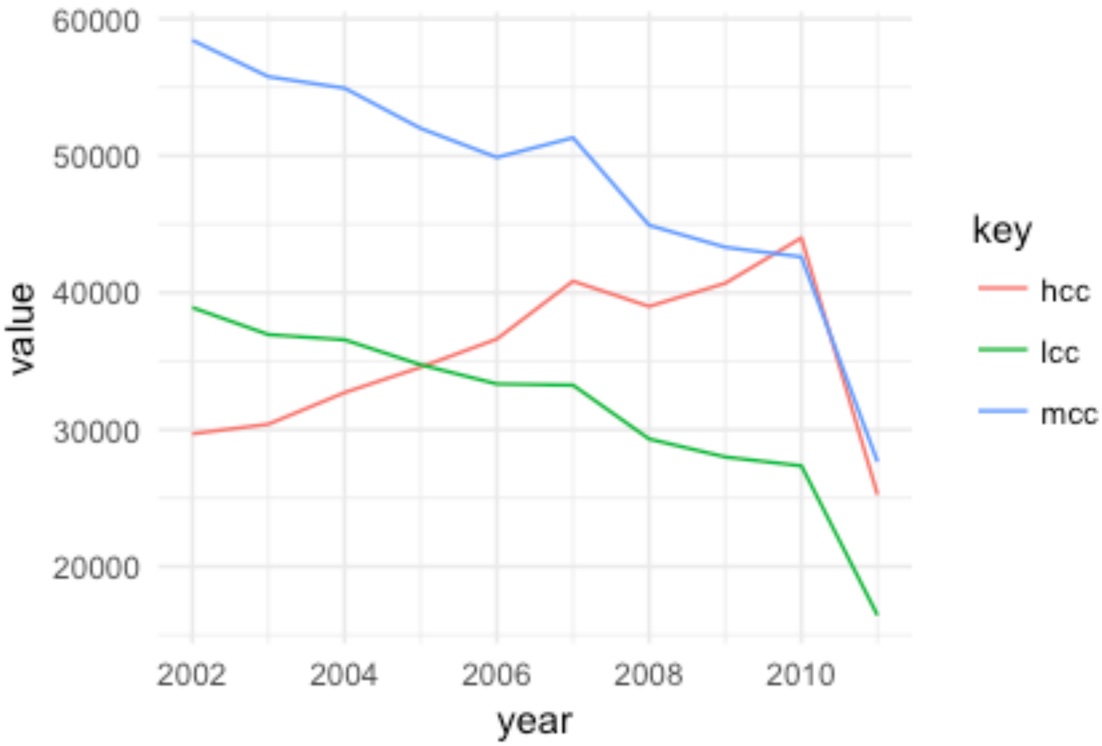

Figure 15: Count of High (hcc), Middle (mcc), and Low (lcc) Blocks over the Study Period

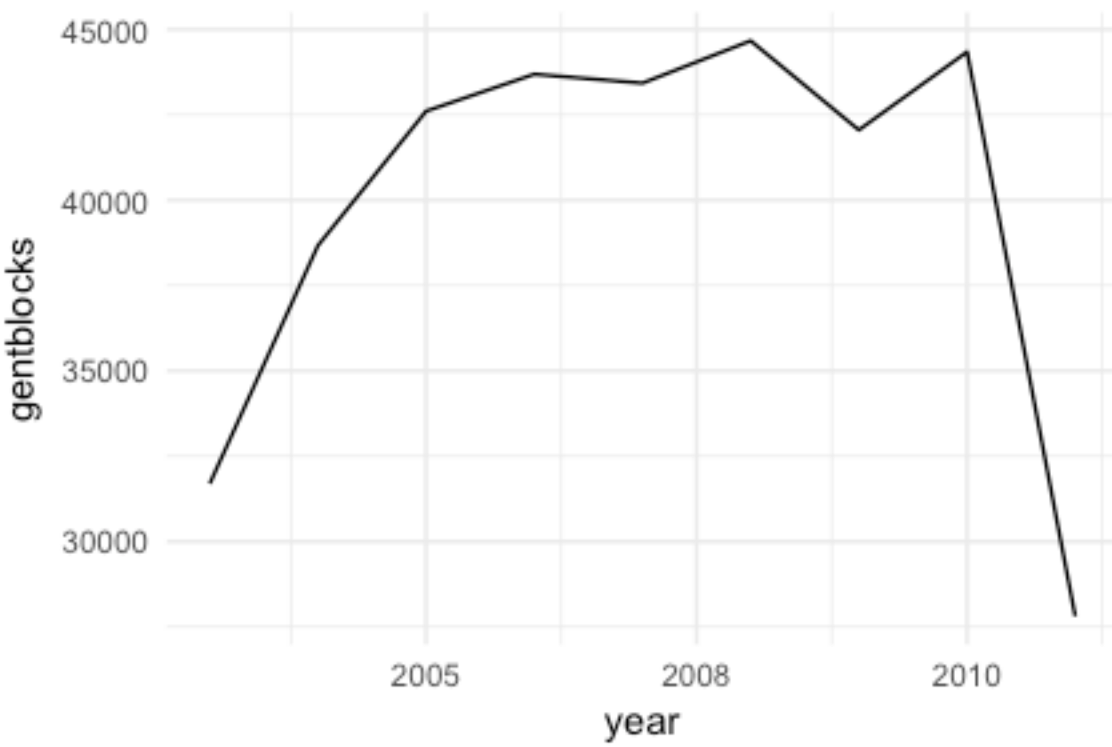

Figure 16: Gentrified Blocks over the Study Period

Table 16: Cusp Model Coefficents with Timberlake's Polarization as the Dependent Variable

	Timberlake (Scaled and Center)			
	1	2	3	4
Intercept	-.11***	-.11***	-.11***	-.14***
	(.02)	(.02)	(.02)	(.02)
Timberlake Squared	-.01	-0.00	-0.00	.02
	(.03)	(.03)	(.03)	(.03)
Timberlake Cubed	.01	.01	.01	.02
	(.01)	(.01)	(.01)	(.01)
Closeness Centrality		.01	.01	.03
		(.02)	(.02)	(.02)
Closeness Centrality Velocity			-.01	
			(.02)	
Timberlake				-.12***
				(.03)
Timberlake Closeness Interaction				-.07***
				(.02)
Observations	1,837	1,837	1,837	1,837
Log Likelihood	-1,630.00	-1,633.00	-1,636.00	-1,618.00
Akaike Inf. Crit.	3,275.00	3,283.00	3,291.00	3,257.00
Bayesian Inf. Crit.	3,314.00	3,327.00	3,340.00	3,312.00
Notes:	*P < .05			
	**P < .01			
	***P < .001			

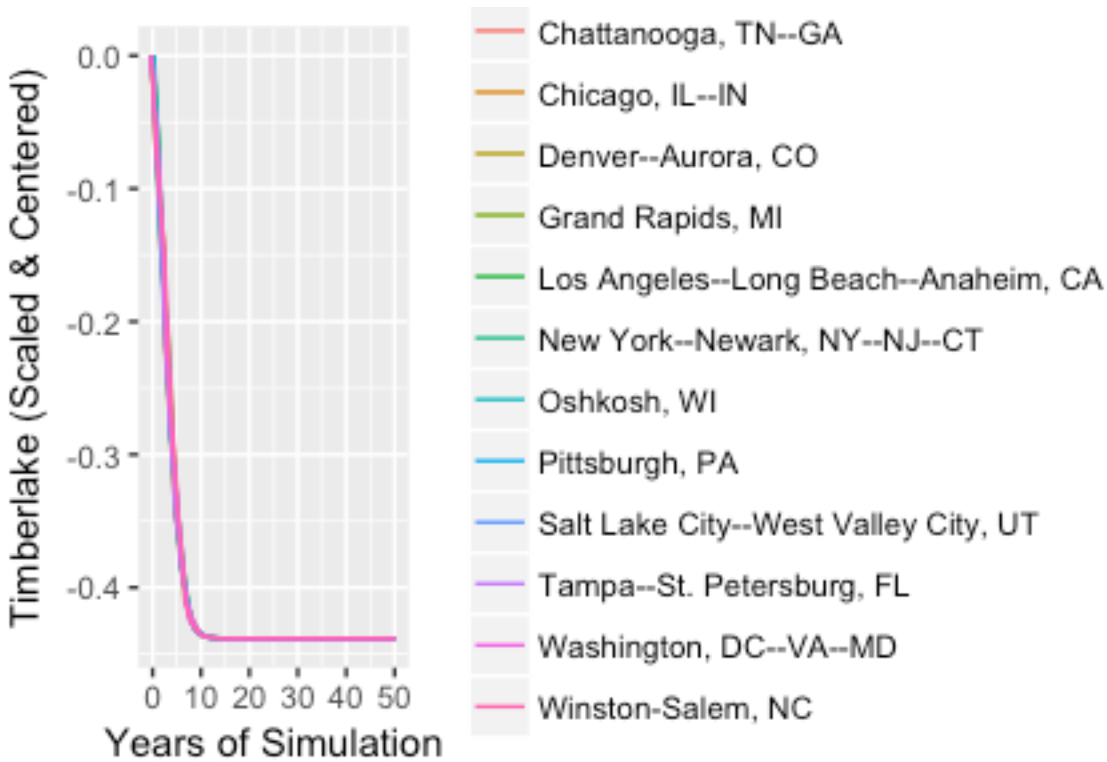

Figure 17: Simulation on Timberlake's Polarization Measure for Representative Cities

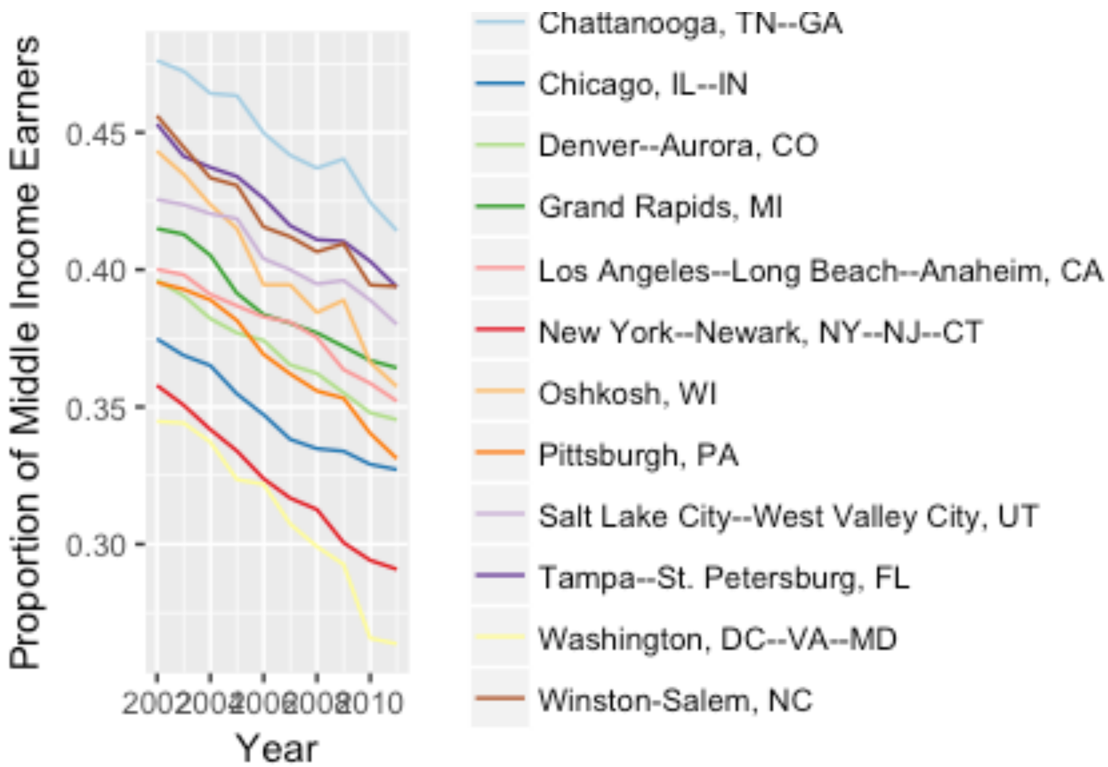

Figure 18: Middle Income Earners over the Study Period in Representative Cities

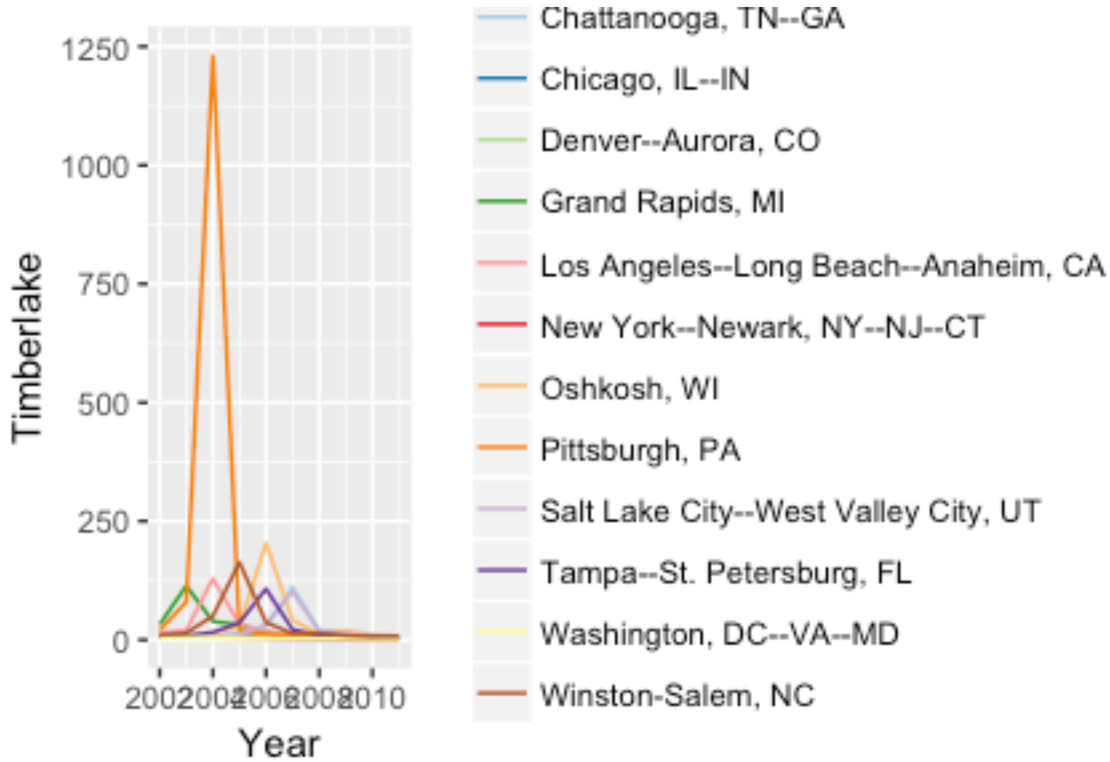

Figure 19: Middle Income Earners over the Study Period

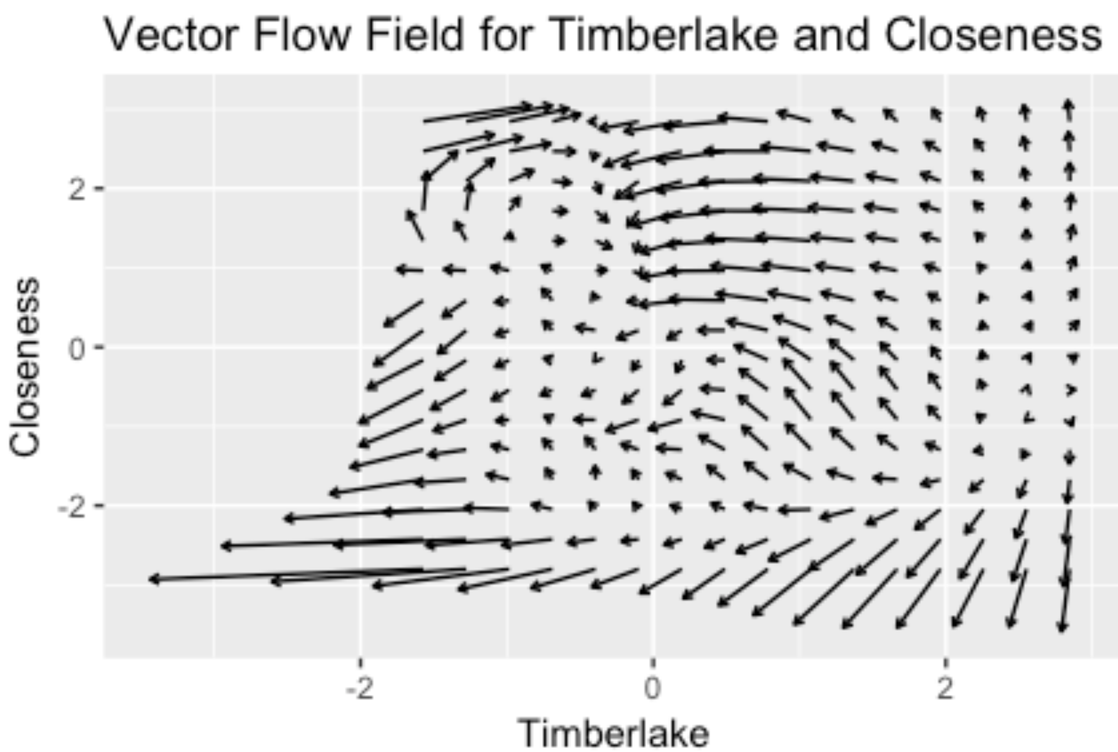

Figure 20: Vector Flow Field for Timberlake and Closeness

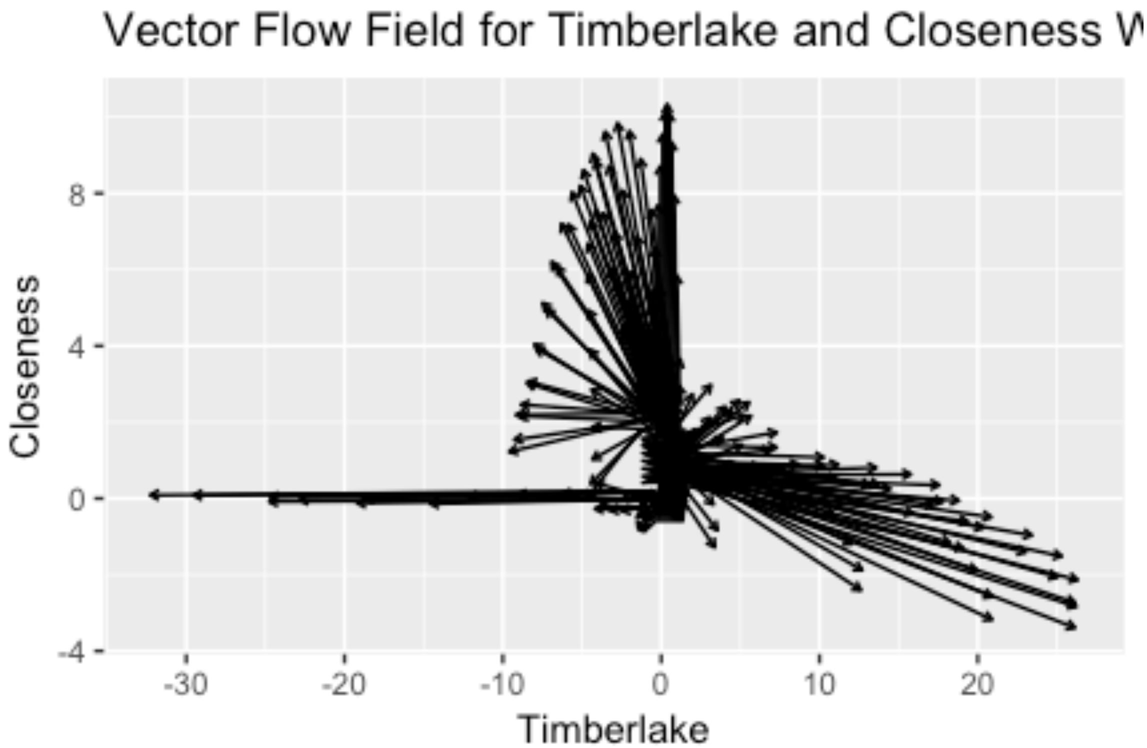

Figure 21: Vector Flow Field for Timberlake and Closeness in Washington D.C.

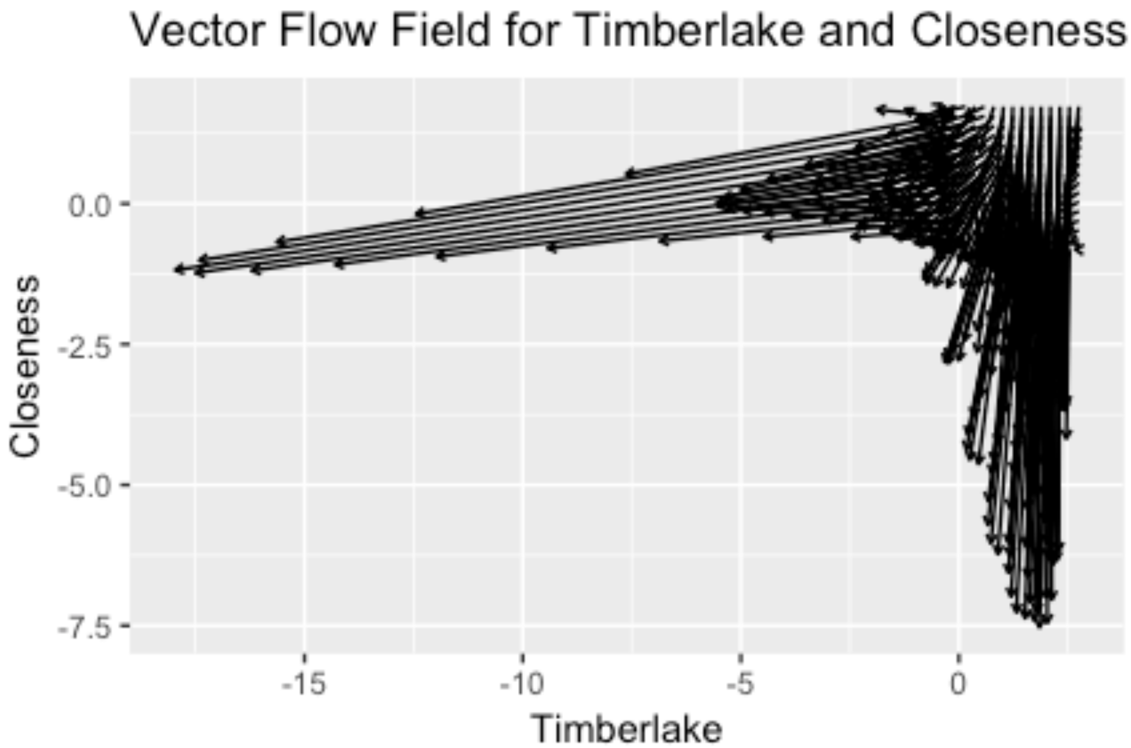

Figure 22: Vector Flow Field for Timberlake and Closeness in Salt Lake City

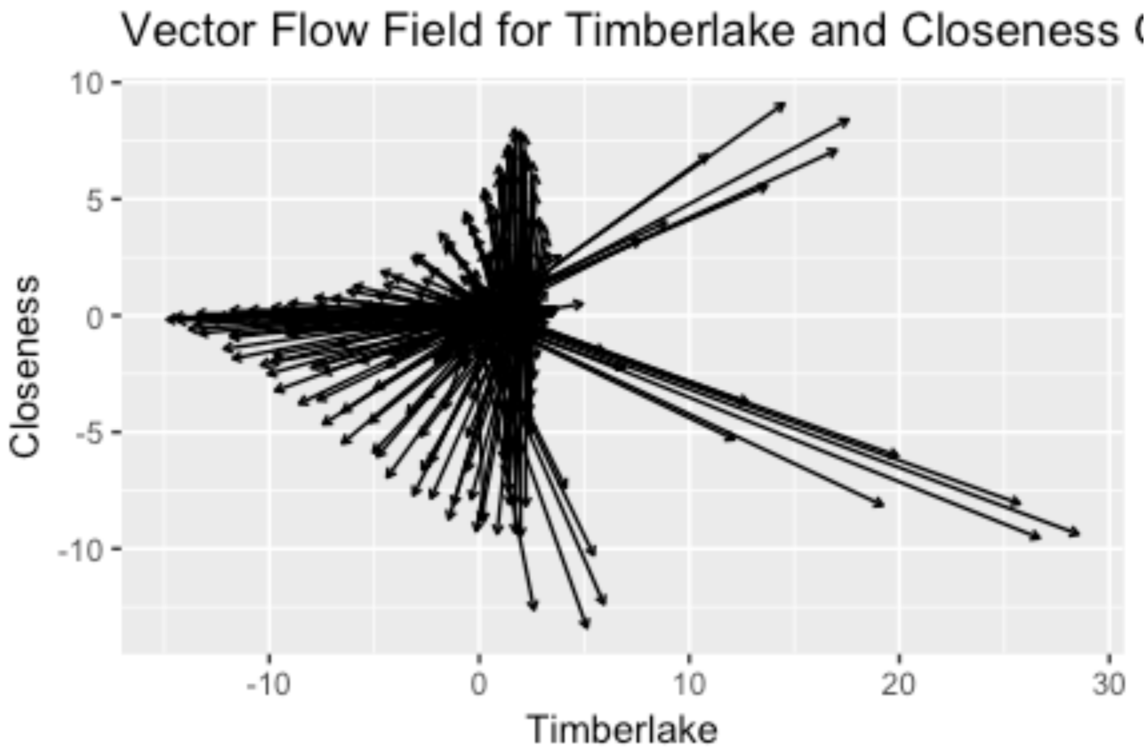

Figure 23: Vector Flow Field for Timberlake and Closeness in Grand Rapids

Table 17: Cusp Model Coefficents with Percentage of Middle Income Blocks as the Dependent Variable

	Middle Income (Scaled and Center)			
	1	2	3	4
Intercept	-.31***	-.32***	-.31***	-.33***
	(.01)	(.01)	(.01)	(.01)
Middle Income Squared	0.00	.01	.01	.03*
	(.01)	(.01)	(.01)	(.01)
Middle Income Cubed	-.01	-.03***	-.04***	.03*
	(.01)	(.01)	(.01)	(.01)
Closeness Centrality		.05***	.04***	.06***
		(.01)	(.01)	(.01)
Closeness Centrality Velocity			.05***	
			(.01)	
Middle Income				-.08***
				(.02)
Middle Income Closeness Interaction				-.04**
				(.01)
Observations	1,837	1,837	1,837	1,837
Log Likelihood	-299.00	-286.00	-277.00	-270.00
Akaike Inf. Crit.	612.00	587.00	573.00	560.00
Bayesian Inf. Crit.	651.00	631.00	622.00	615.00

Notes: *P < .05
**P < .01
***P < .001

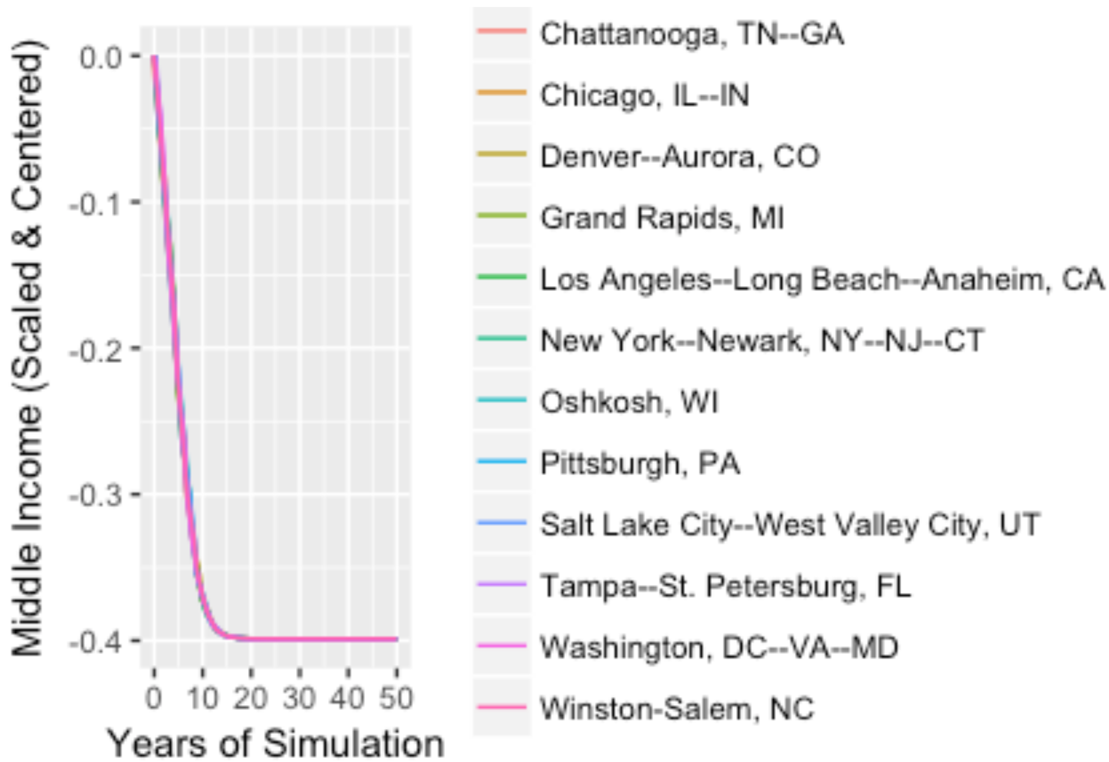

Figure 24: Middle Income Simulations

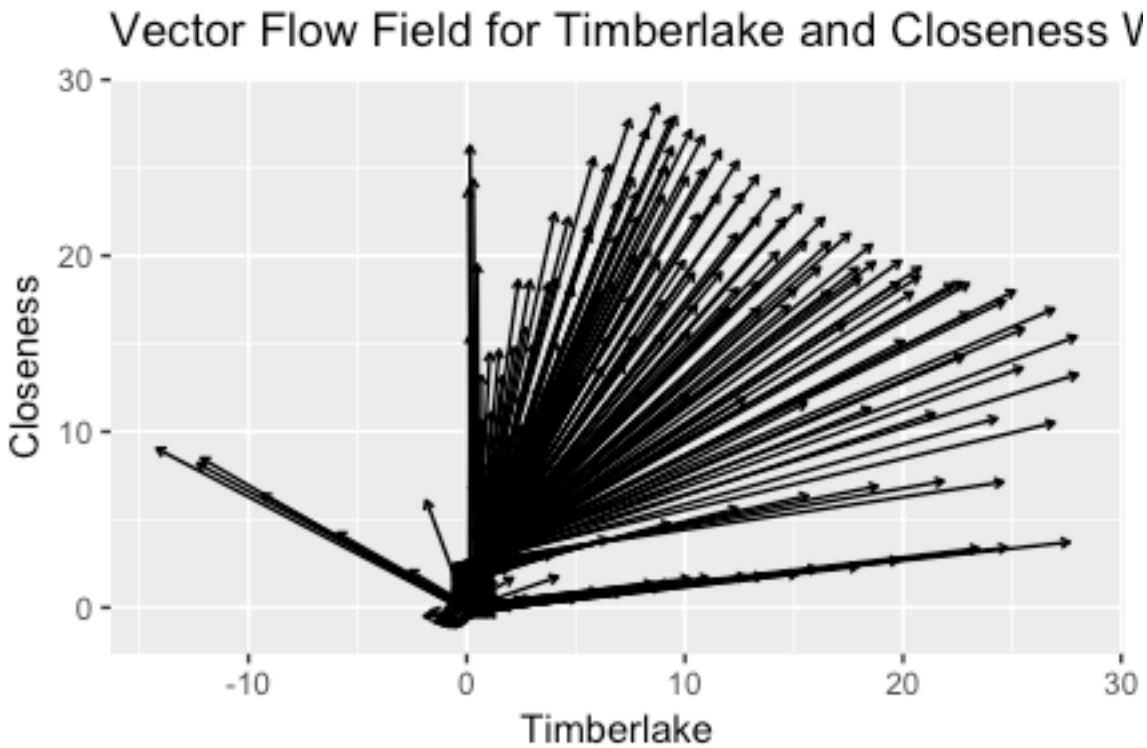

Figure 25: Vector Flow Field for Middle Income Blocks and Closeness in Washington D.C.

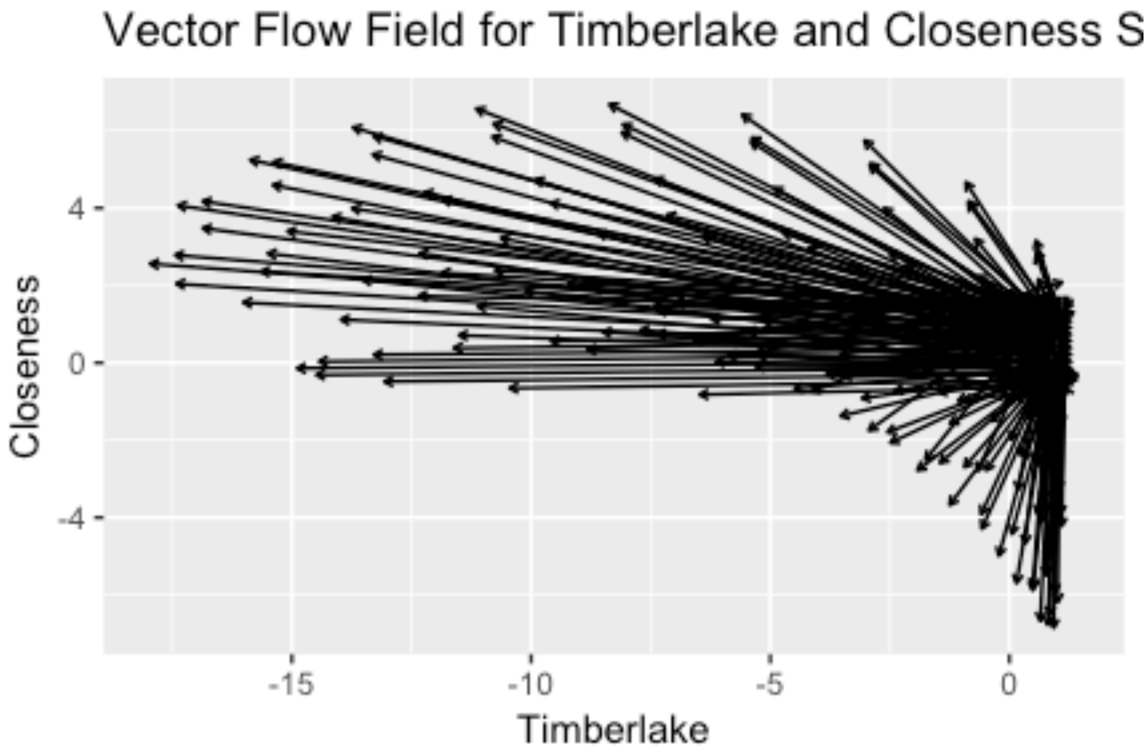

Figure 26: Vector Flow Field for Middle Income Blocks and Closeness in Salt Lake City

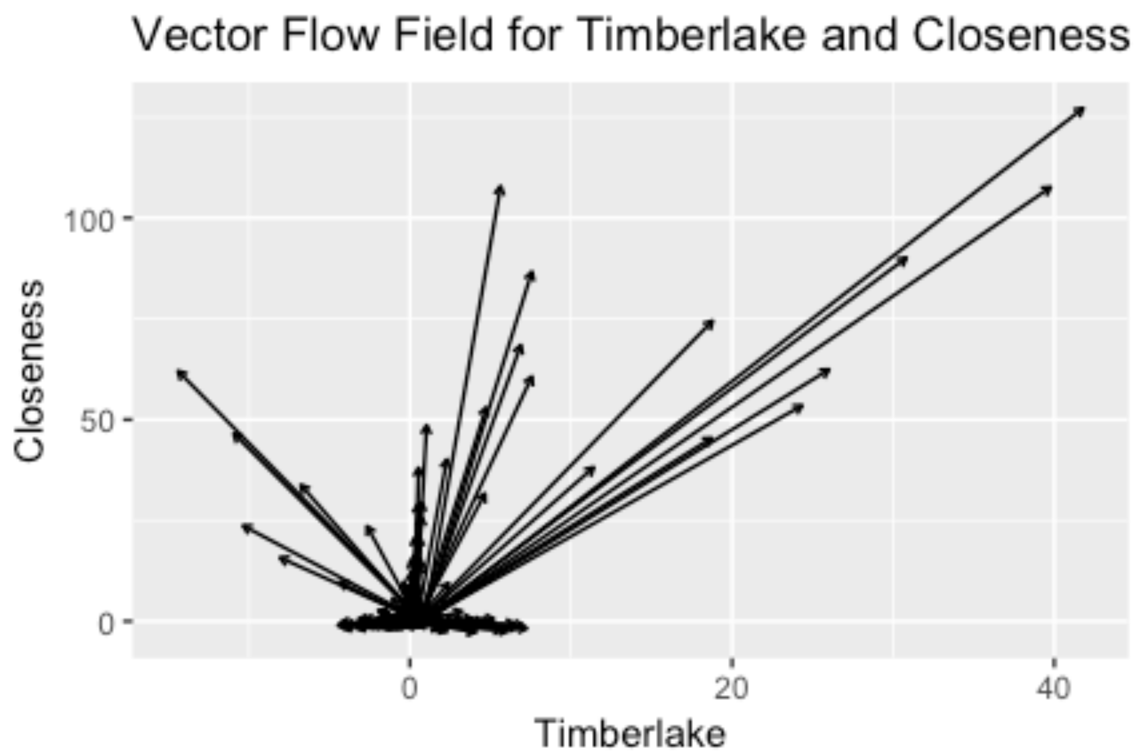

Figure 27: Vector Flow Field for Middle Income Blocks and Closeness in Grand Rapids

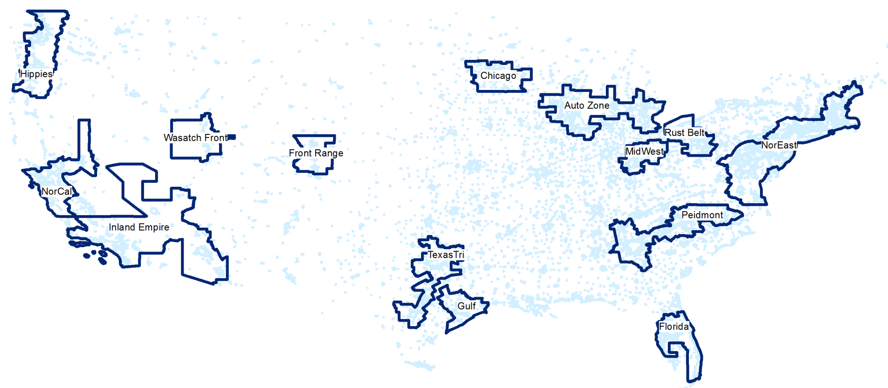

Figure 28: Mega Regions

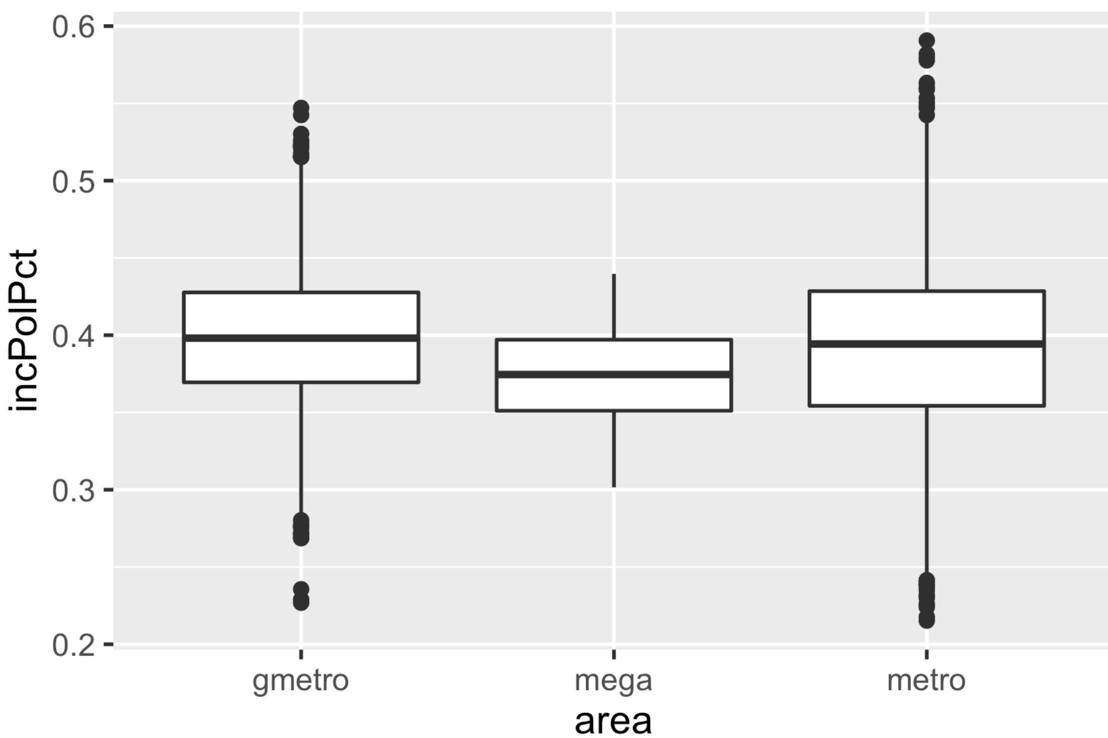

Figure 29: Middle Income Earner Boxplots by Agglomeration Type

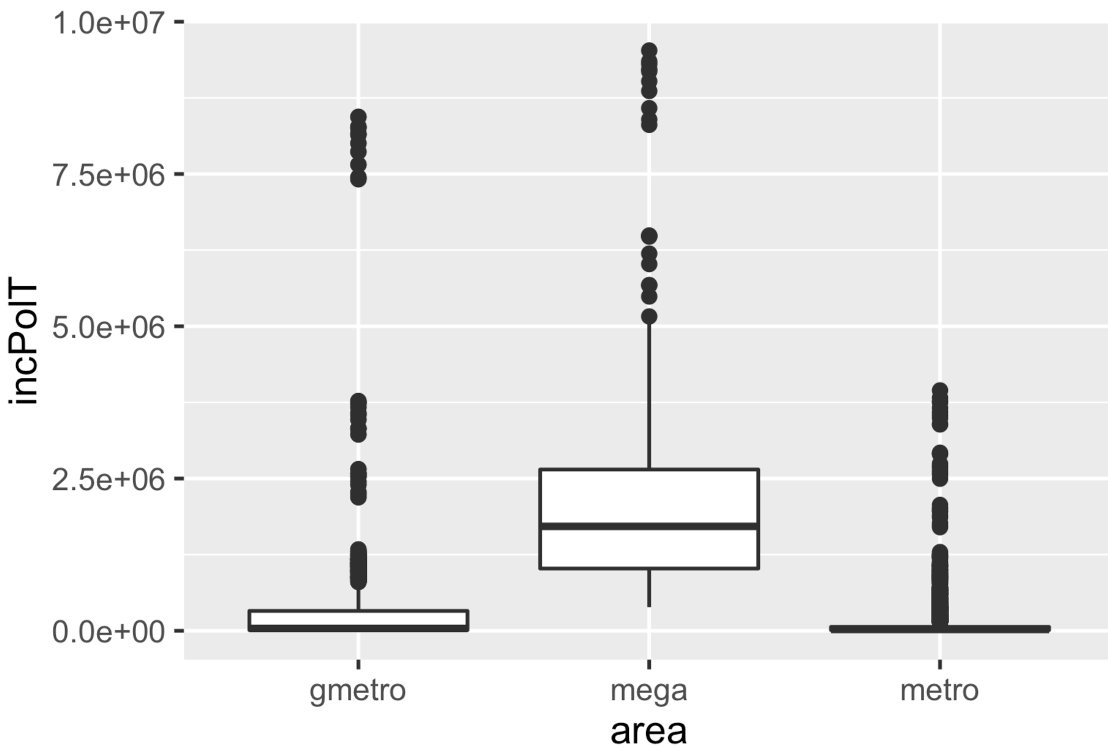

Figure 30: Timberlake's Polarization Boxplots by Agglomeration Type

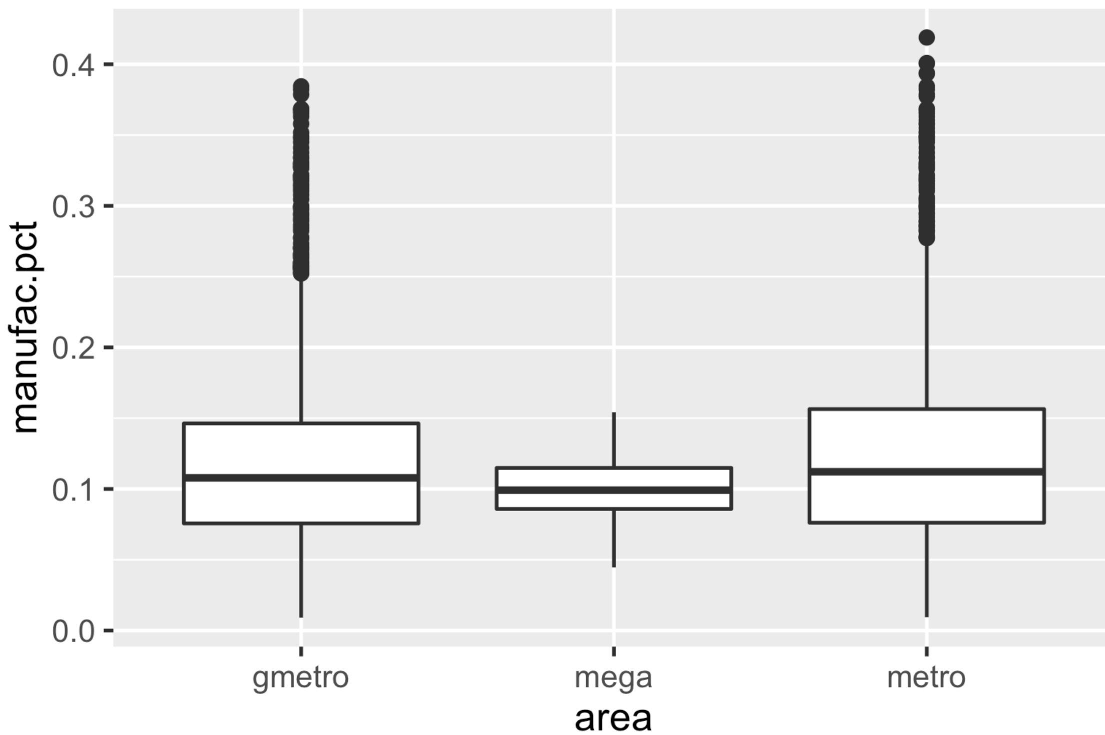

Figure 31: Manufacturing Percentage Boxplots by Agglomeration Type

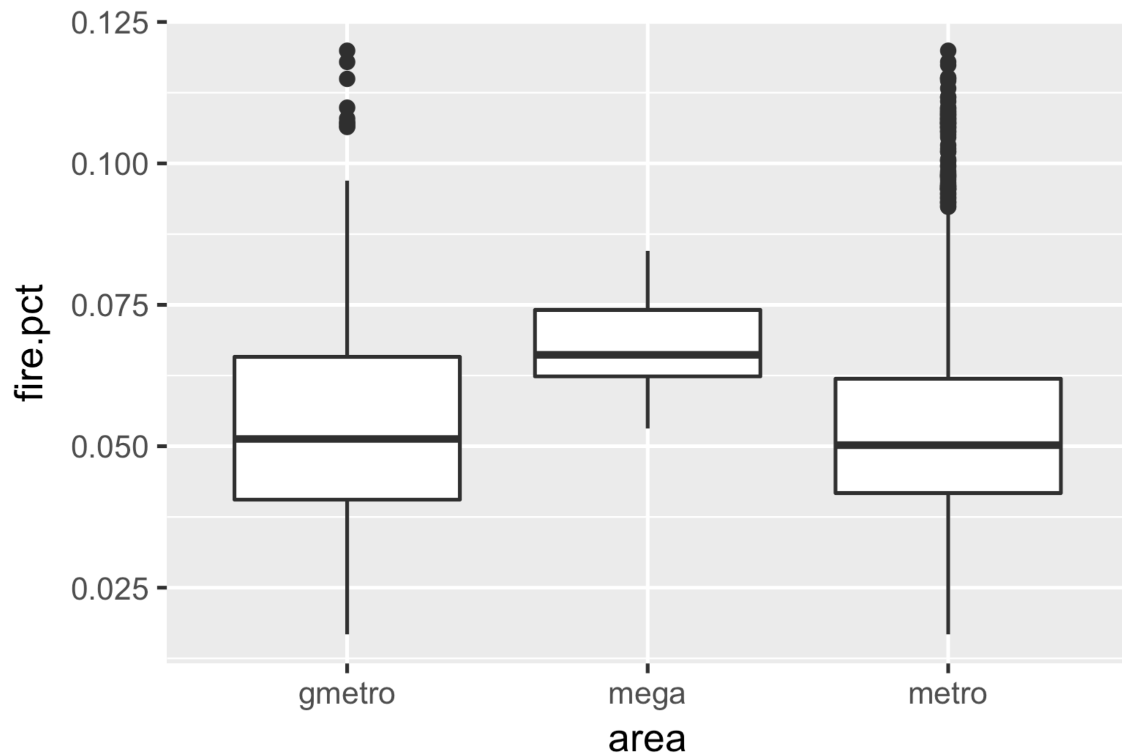

Figure 32: F.I.R.E. Percentage Boxplots by Agglomeration Type

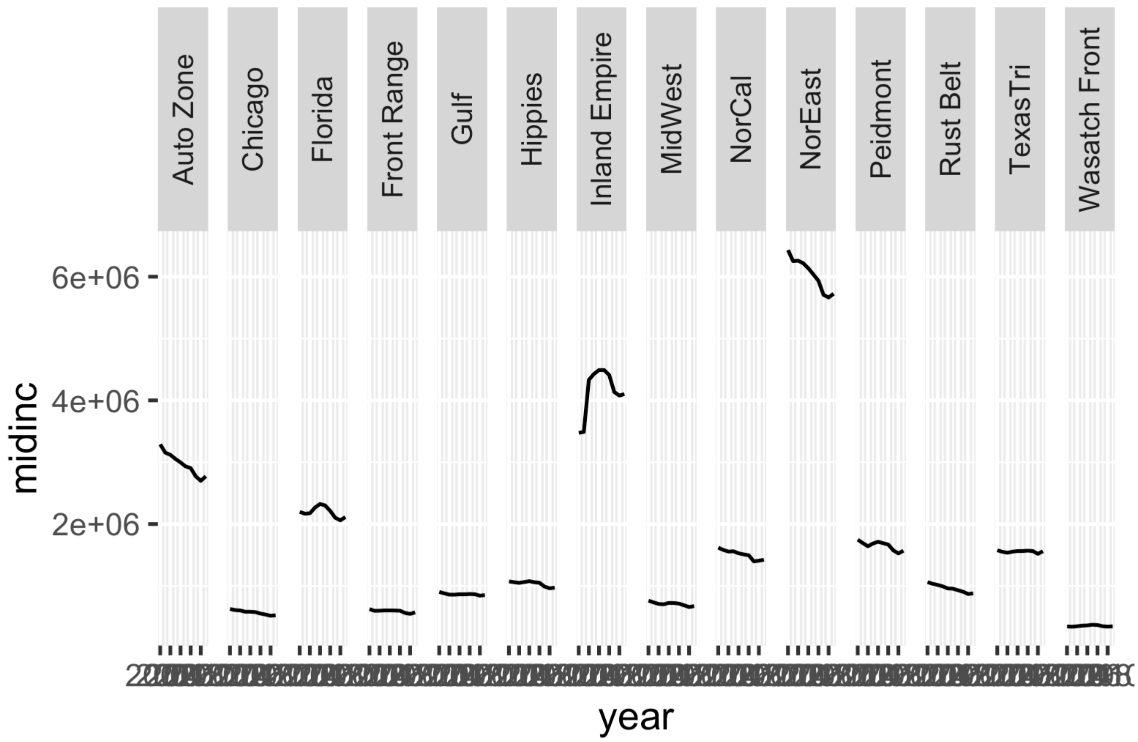

Figure 33: Middle Income Earners over Time

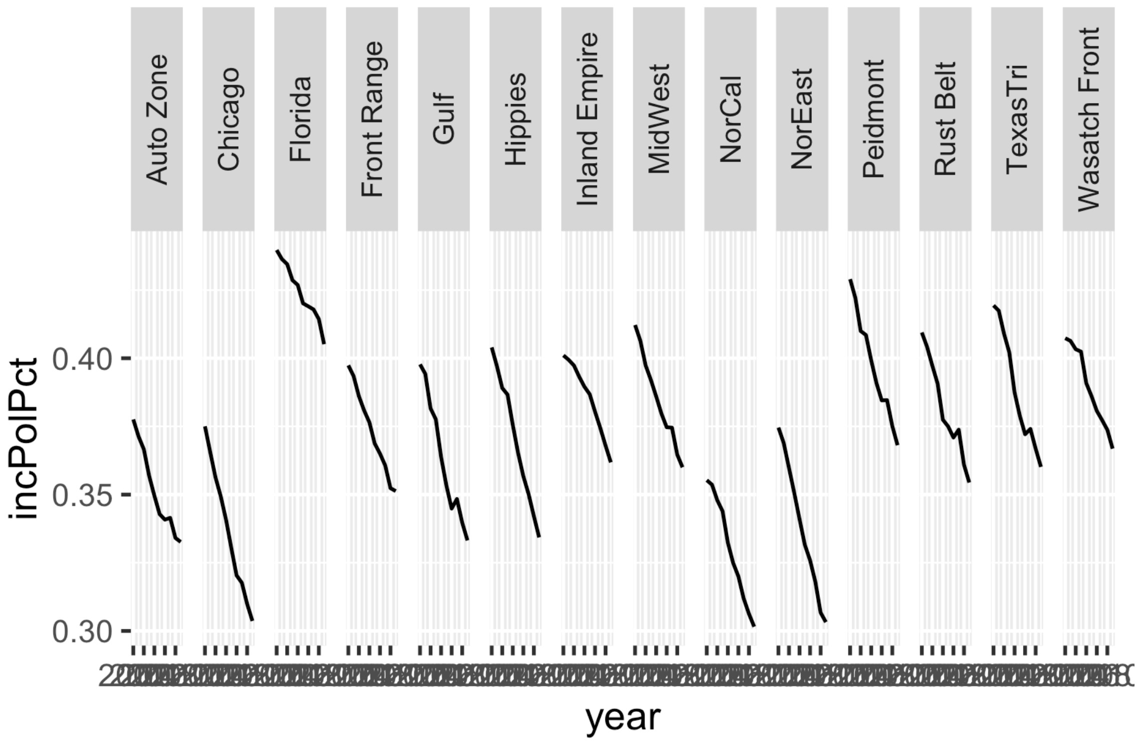

Figure 34: Middle Income Percentage over Time

Table 18: Summary Statistics for Mega-regions

Area	Middle Income Earners	Timberlake Income Polarization	Pct. of Mid Income Earners	F.I.R.E	F.I.R.E %	Manufacturing	Manufacturing %	Management	Management %
Auto Zone	-515989	-10.02	-0.045	-53775	-0.004	-365527	-0.037	4411	0.001
Chicago	-102179	-5.53	-0.071	8588	0.002	-22772	-0.017	-10356	-0.007
Florida	-83403	-0.12	-0.035	18015	0.001	-78045	-0.018	12514	0.002
Front Range	-52874	-7.20	-0.046	-8435	-0.008	-39496	-0.027	10245	0.006
Gulf	-51431	-11.56	-0.065	3463	-0.005	-2117	-0.012	12751	0.005
Hippies	-101757	-7.70	-0.070	-13980	-0.010	-20360	-0.017	5846	0.001
Inland Empire	627326	-20.61	-0.039	154153	0.000	-119389	-0.039	-10595	-0.006
MidWest	-87020	-183.30	-0.052	1182	0.000	-63410	-0.036	14509	0.007
NorCal	-194896	-3.01	-0.054	-31502	-0.009	-81443	-0.021	-16527	-0.004
NorEast	-706764	-6.00	-0.071	-49826	-0.010	-411326	-0.030	60553	0.002
Peidmont	-178171	-26.46	-0.061	9949	-0.001	-139474	-0.039	-13795	-0.004
Rust Belt	-182315	-6.17	-0.055	-16665	-0.004	-97810	-0.033	23151	0.010
TexasTri	-15804	-31.01	-0.059	49195	0.001	-57727	-0.027	25765	0.005
Wasatch Front	2251	7.70	-0.041	4445	-0.002	-3319	-0.016	-3300	-0.006

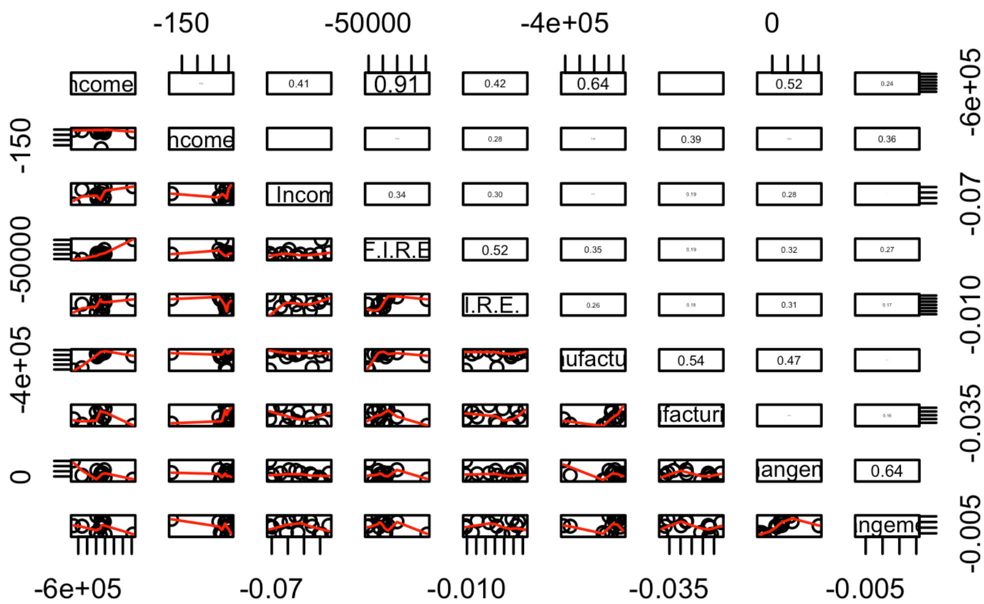

Figure 35: Difference Score Correlations: Economic Structure

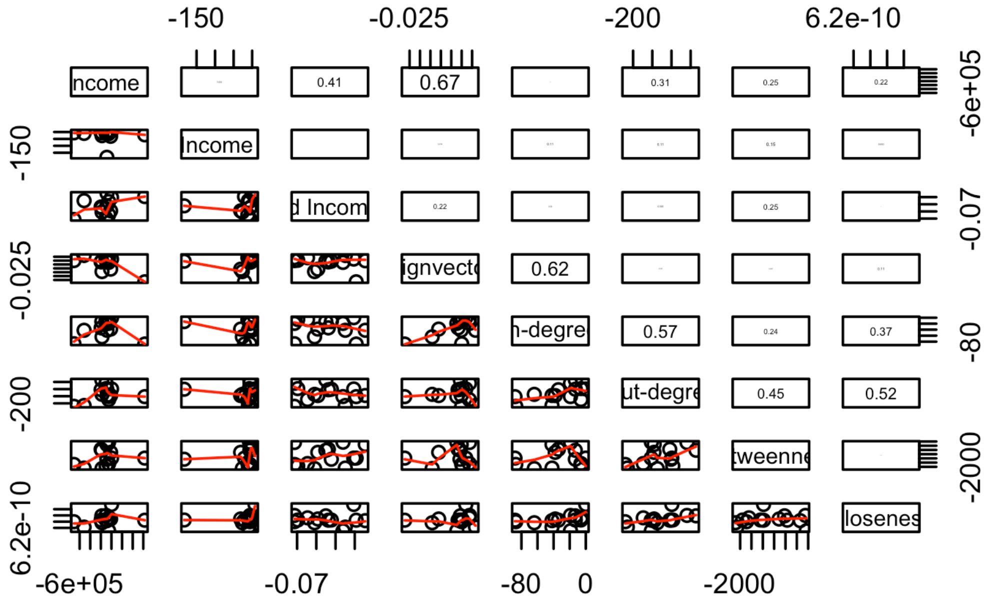

Figure 36: Difference Score Correlations: Centrality

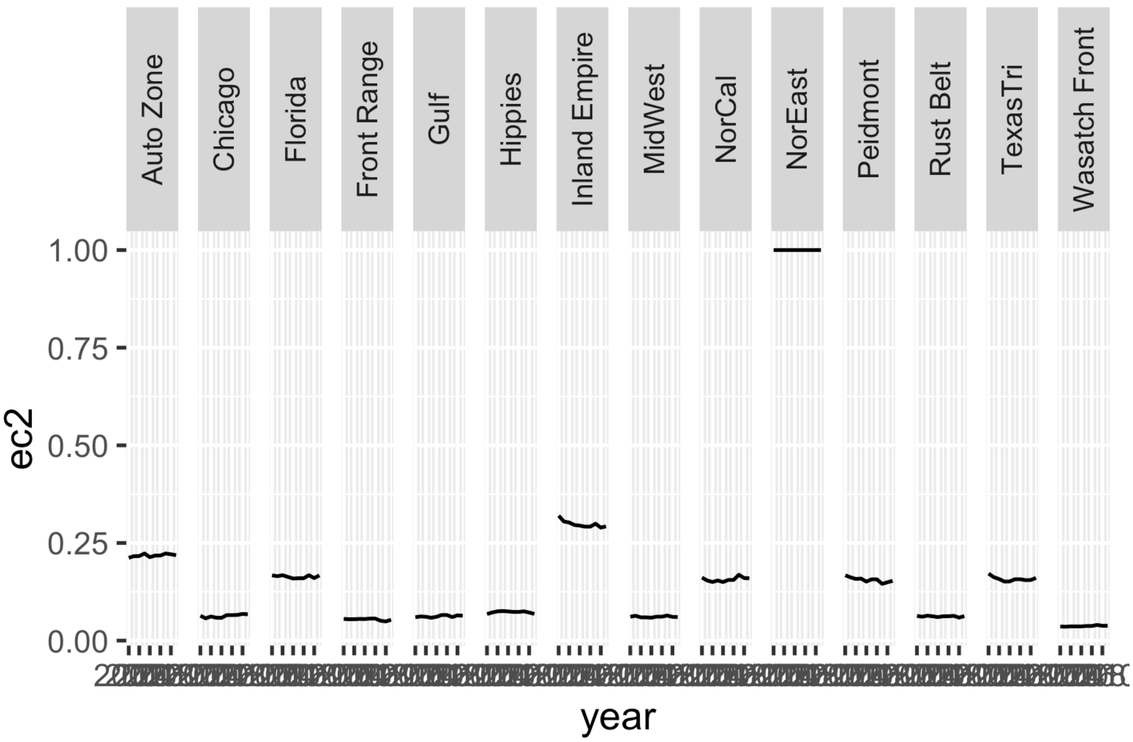

Figure 37: Eignvector Centrality over Time

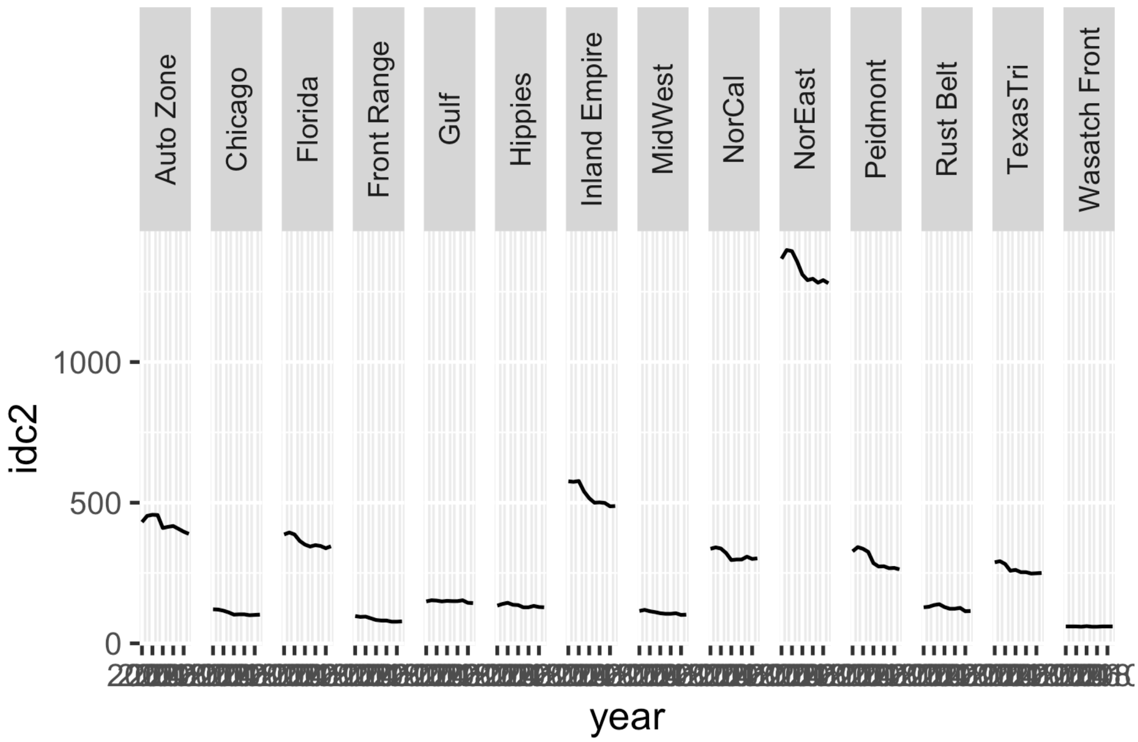

Figure 38: In-Degree Centrality over Time

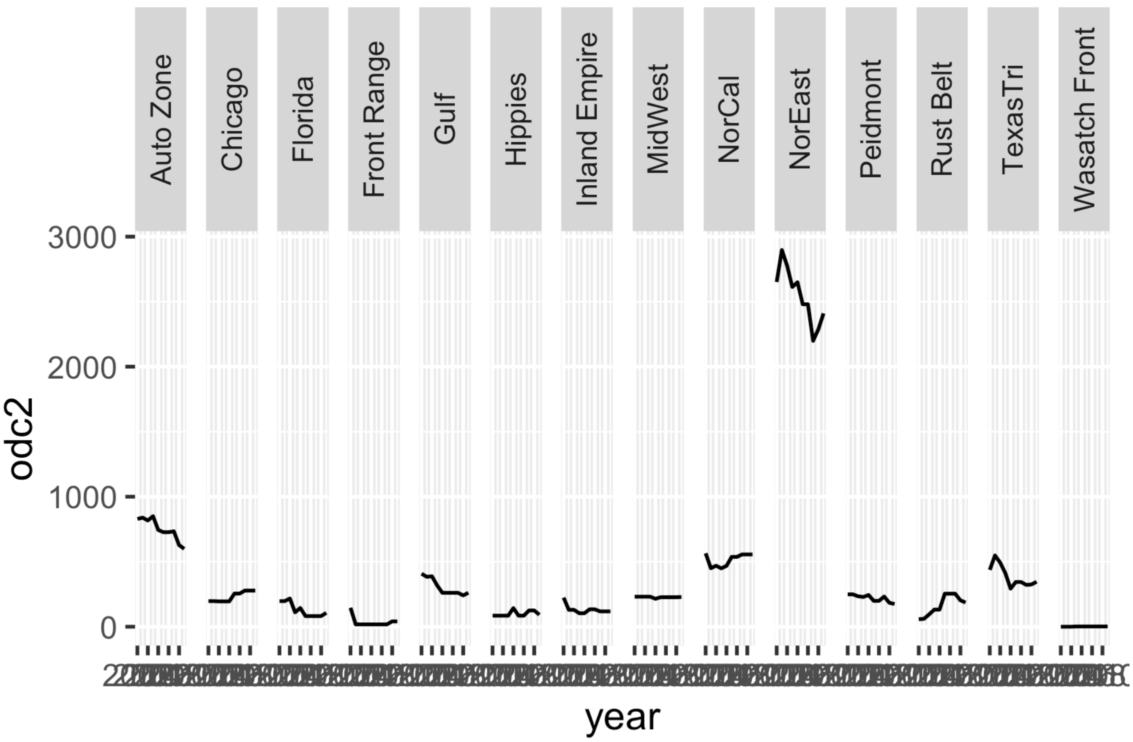

Figure 39: Out-Degree Centrality over Time

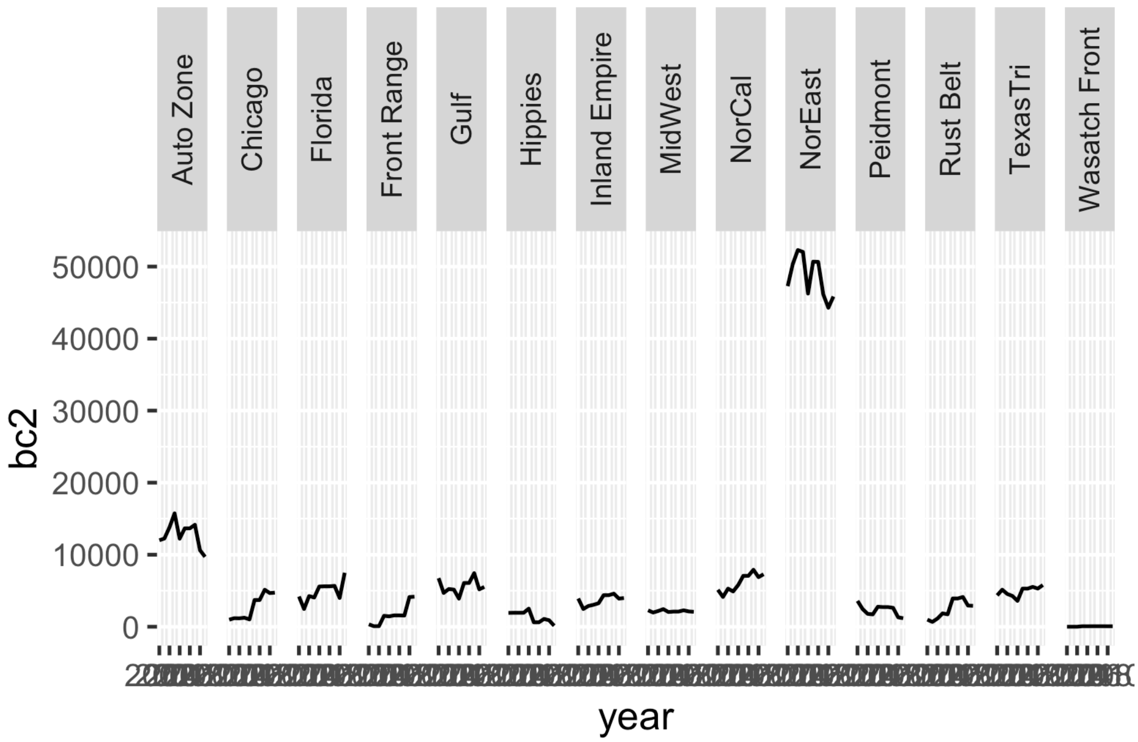

Figure 40: Betweeness Centrality over Time

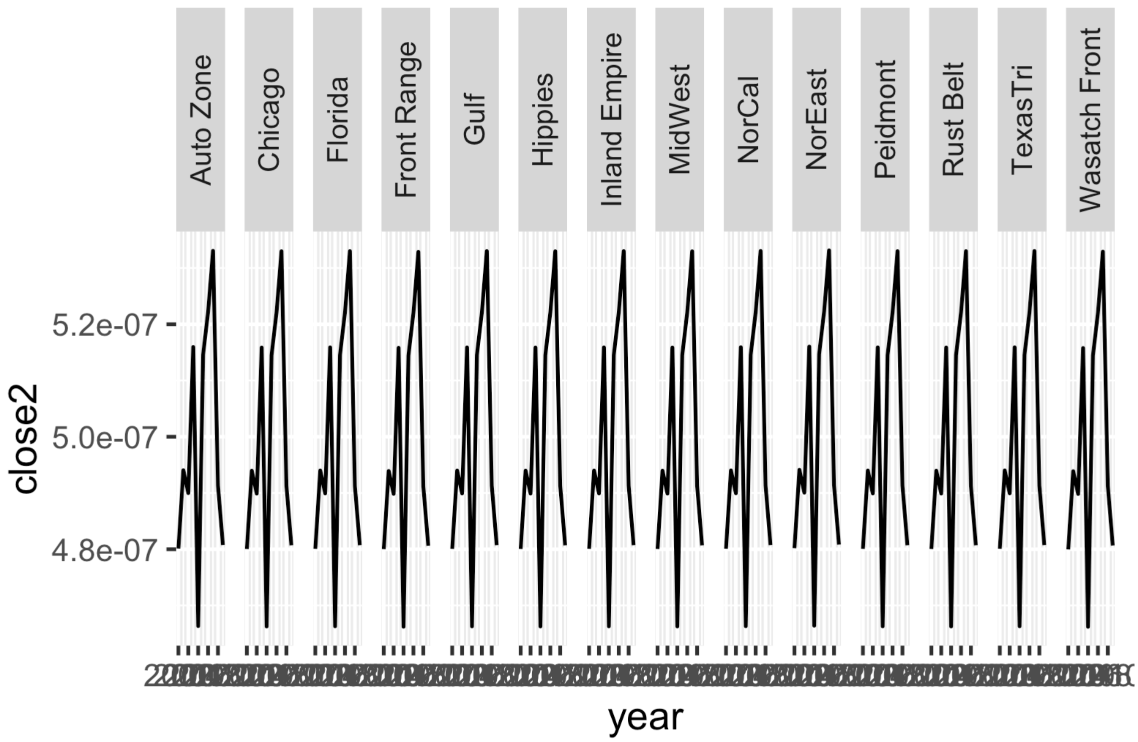

Figure 41: Closeness Centrality over Time

DISCUSSION

Since Hamnett's critique of the Polarization Hypothesis, the literature has been focused on showing either that Polarization (as defined by middle class declines and simultaneous polar growth) exists, or explaining reasons why cities do not display all of the theorized components (Hamnett 1996). Most research has left Hamnett's critique of the polarization definition alone. This dissertation delves into the nuance of defining polarization by using models across multiple dimensions of polarization to see where the definitions of polarization fall flat.

The usual measure of polarization is the size of the middle class, which has been declining in the U.S. for a considerable period of time. Sassen began her research project into polarization in the mid -1980s after seeing declines in the middle class (Sassen 1991). Many papers followed Sassen, illustrating time and again that the middle class was continuing its decline. This paper continues that tradition showing that during the study period there was a continual decline in the middle class.

While the middle class is still in decline, that decline does not necessarily equal polarization. Both Hamnett and Timberlake focused attention to the poles of the income distribution as a key aspect of polarization. The results of this paper show that while the middle class has decreased, there is no corresponding balance to the poles of the income distribution; rather the gains have all gone to the upper class. Sassen's hypothesis of the idea of APS generating both high and low paying jobs is not borne out by the evidence presented in this paper.

This dissertation illustrates that the assumptions of about APS effects on the lower part of the income distribution is where the Polarization Hypothesis falls short. The theory states that an increase in APS workers generates low wage jobs to provide services to the highly paid service workers (Sassen 1991; Abrahamson 2004). This research shows that, like the middle class, the lower wage earners are also in decline. Since the data are comprised of employed individuals it is likely that there are fewer low wage jobs due to jobs being replaced by overseas workers or automation.

The decline in the middle and low earning groups is not limited to their percentage of employment, but also to the spatial structure of the cities. The percentage of areas that are predominantly inhabited by these groups also shows declines over time. According to the Polarization Hypothesis, we should see smaller clusters of middle and low income areas as the high wage APS workers gentrify areas. The results fall in line with the Hypothesis, decreasing over time and with a general increase in the amount of gentrification. The growth in the high income areas is associated with all of the aspects the theory ties to increased APS workers, including the position of the city in the Global City Network.

The impact of the position in the network of world cities that a specific city occupies does not seem to have much impact on the low or middle class areas, suggesting that most of the changes to spatial structure are being generated by the predominance of the upper income groups (Abrahamson 2004). The power of the wealthy in remaking the city in their own image is supported by this paper. The power of the APS workers appears to be primarily focused on the smaller metro scales. In almost every analysis the standardized effect sizes are smaller in the larger geographic areas which confirms previous findings that geographic scale matters (Fainstein 2000).

The one measure that doesn't seem to be impacted by scale is areas dominated by low and across geographic scales, but there is a great deal of variation with the high income areas.

This finding supports the work of Taylor (2006) and his focus on the city centers as the key command and control areas of the economy. Not only are these smaller high income areas more heavily impacted by APS employment, but also by connections to the world city network. Although the larger urban agglomerations contain more connections than the smaller areas, the correlations are not as great, indicating position in the network has a greater impact on the smaller areas and therefore the research on the connection between polarization and a city's articulation with the global economy should be focused at the smaller geographic scale.

The different measurements of network position support the work of Timberlake's (2012) choice of closeness centrality. Closeness centrality indicates how quickly one can get to all other points on the network, and is the most consistently significant variable in the analyses presented here. Closeness is the best approximation of position in the network. Other measures of centrality, namely in-degree and out-degree, have a more direct theoretical linkage to change in city structure because they are directional. Directional measures can be thought of as directly increasing the resources moving into the APSs of a city, increasing capital and thereby the power to modify the urban fabric. Measures like closeness are not directional and cannot be thought of in terms of pushing or pulling capital. Instead, closeness centrality indicates position, and the ability to push or pull capital throughout the network. According to Friedman it is this position that is expected to generate polarization (Friedmann 1986). Instead of the Matthew principle (to he who hath shall receive), it is more likely that the cities with the greatest flexibility in the network (which corresponds to the generation of capital) are those most likely to witness polarization occurring due to the impact of highly paid transnational class at the helm of the global economy.

One of the hypotheses of this paper was that the position in the global economy could shift into, or out of, a polarization trajectory. Again this is a nuance brought up in Hamnett's critique that New York, London and Tokyo are not representative of all the cities in the world, or globally central cities. This dissertation's findings indicate that New York and other U.S. based cities are all on similar trajectories, regardless of position, power or prestige within the global network of cities. The declines in the middle class appear to be omnipresent. The declines in the middle class can also be seen in the largest geographic areas, mega regions.

The Mega regions are argued to be the appropriate geographic unit of analysis for research on global processes (Florida, Gulden, and Mellander 2008). This research demonstrates that Mega regions have a higher proportion of APS employment than the smaller geographic regions, supporting Lang (2003) and Garreau's (1991) research that more service sector jobs are moving outside the core urban areas. The Mega regions experienced the same declines in the middle class as the other urban areas, but do not express the same imbalance in the poles of the income distribution. This indicates that only when taking into account a full economically integrated area does polarization manifest itself, with both middle class declines and balanced poles. However, aggregating to such a large geographic level masks much of the internal variation as Burgers (1996) critiqued Hamnett for in his lumping of the Randstadt of the Netherlands into a single area. As Lobao, Hooks, and Tickamyer (2007) argue, the questions being researched need to drive the spatial unit of analysis. If one is looking at power concentrations then smaller city areas should be used Taylor (2006), but if the desire it to investigate a coherent economic unit, mega regions seem appropriate. The need is for researchers to clearly articulate the geographic boundaries, and discuss the information loss associated with the boundaries chosen and discuss the theoretical relevance of the chosen geography.

This research has a number of data issues that should color the implications of the finding, namely the network data are retrospective, the income categories are fixed and not intuitive breaks, the dataset only considers individual income, not household income, and is only for urban areas in the United States. While these issues are problematic, the fact that the dataset is consistent does provide a unique opportunity to evaluate the different aspects of polarization in a consistent manner.

Taking all of the evidence together this paper indicates that polarization is an extremely nuanced topic, and that a key component of that nuance is geography. Individuals continuing in this vein of research need to consider carefully how to define polarization and what the appropriate unit of geography is for their analysis. The GWAC focuses on individual cities and their linkages because they are the command and control points, but the impact can be much larger, and many of those articulation points have moved out of the inner city areas. The polarization presented in *The Global City* (Sassen 1991) is most likely an artifact of the unit of analysis. That is not to say that declines in the middle class are not a problem, but they exist at all geographic scales in the U.S., not just the globally central cities, or inner cities.

CONCLUSION

This paper has demonstrated that polarization is a multifaceted phenomenon. Economic structure, position in the global network of cities, geographic scale, and time all have unique interactions on polarization, and the interaction change based on the type of polarization being measured.

The components of polarization include the size of the middle class, the balance of the poles of the income distribution, gentrification and spatial organization. Much of the previous work on the Polarization Hypothesis could be an artifact of the geographic scale used in the analysis. In the future, issues of time and geographic scale need to be clearly defined and theoretically justified.

APPENDIX A

DISCUSSION OF INCOME MEASUREMENTS

The datasets used in studies of polarization vary. They most often include information on income and/or occupation at multiple points in time (Vaattovaara and Kortteinen 2003; Baum 1997; Borel-Saladin and Crankshaw 2009; Wessel 2000; Hamnett 1996; Burgers 1996; Kempen 1994; Walks 2001; Sassen 1991; Baum 1999; Chiu and Lui 2004). Timberlake et al. (2012) is unique in that they looked at the variation over multiple urban areas (metropolitan statistical areas) at a single time, and used income aggregated to a household level. As this study attempts to analyze polarization at both the breadth of Timberlake's spatial variation, and match it with temporal variation, I use a lesser known census product which uses personal income as opposed to household income. This appendix is designed to evaluate the differences between these measures of the income distribution.

The U.S. Census has three primary ways of reporting income: household, family and individual. A household is defined as a group of people living together. A family is a household where the members are related to each other through ties like blood, marriage or adoption. Both of these reporting structures are aggregates, summing the income of all individuals in the home. The assumption for this reporting structure is that the income itself is communal, all flowing into a single repository for use by the entire household.

Personal income reports assume that there is no aggregation of income to the household level (be it related or unrelated household members). One of the issues raised by

Burgers (1996) in his critique of Hamnett's (1996) article using personal income was that it left out those individuals who had no personal income but relied instead on the income from other household members, individuals such as stay at home parents, or non-income-generating children. This argument primarily applies to households that are family based, which are the majority of all households in the U.S.

One of the issues in generating an income distribution is how do these three measures correlate with each other, or are they comparable/interchangeable? The LEHD dataset used in this paper counts the number of individuals with incomes less than or equal to $1,250 per month, those earning between $1,250-$3,333 per month and those earning more than $3,333 per month. In Timberlake's polarization research the income distribution of households was used, where the working class was assumed to be the lowest quintile and the upper class the highest quintile. The middle class then comprised the remaining three quintiles. The difference between this measure and the breakdown of the LEHD seems to be quite different and non-comparable.

The following analysis shows that there is significant correlation between these different views. This analysis compares the LEHD data, with the Current Population Survey (CPS) for personal income and the American Communities Survey (ACS) data on household and family income. The CPS dataset spans the years 2002-2011 and counts the number of individuals in each income group. The income groups are $2,500 ranges starting at $0, and are right truncated at $100,000+. The ACS data come from the 1-year estimate files for the years 2005-2008, and groups household and family incomes into the following groups:

- Less than $10,000
- $10k - $15K
- $15K - $25K

- $25k - $35K
- $35k - $50K
- $50k - $75K
- $100K - $150K
- $150 - $200K
- $200K +

To make the disparate datasets comparable, the cumulative percentage of each income group was calculated for each year. Using the cumulative distribution cut offs of less than 0.2 for the lower quintile and greater than 0.8 for the upper quintile all the data can be compared in terms of an income distribution structure of low, middle and high. Tables 19 - 21 display the percentages of each income group, and that the LEHD's middle income group is consistently higher than any other dataset.

However, the correlations between the different datasets is very high, as illustrated in the scatter plot matrix in Figures 43-45 which looks at the correlation between each dataset and income group. This high correlation shows that while the LEHD is a unique dataset with an income grouping structure that is quite different from those used in other studies, it can accurately represent the income distribution of the United States.

The data were joined on year and metro area to make sure that there was an apples to apples comparison. The resulting dataset contained information on 72 metro areas compared to the 326 used in the rest of this paper. The best fitting model by AIC is the LEHD model (Table 22) . The primary differences between the models are that F.I.R.E. is a significant predictor for middle class households, but not for income earners during 2005-2008. The direction of the correlation is not consistent with the Polarization Hypothesis. The variables manufacturing and management employment are highly significant in the LEHD data and at similar levels as found in the main body of this paper. Modifying the range of household income has little effect on the model coefficients.

Table 19: Low Income Percentages Across Different Data Sources

LEHD	Personal Income	Family Income	Household Income	year	order
0.27	0.16	0.13	0.18	2005	1
0.27	0.19	0.13	0.17	2006	1
0.26	0.19	0.13	0.17	2007	1
0.25	0.19	0.14	0.17	2008	1

Table 20: Middle Income Percentages Across Different Data Sources

LEHD	Personal Income	Family Income	Household Income	year	order
0.38	0.61	0.54	0.56	2005	2
0.37	0.60	0.53	0.55	2006	2
0.36	0.60	0.66	0.54	2007	2
0.35	0.61	0.64	0.53	2008	2

Table 21: High Income Percentages Across Different Data Sources

LEHD	Personal Income	Family Income	Household Income	year	order
0.35	0.23	0.32	0.26	2005	3
0.37	0.21	0.34	0.27	2006	3
0.38	0.22	0.21	0.29	2007	3
0.39	0.20	0.22	0.30	2008	3

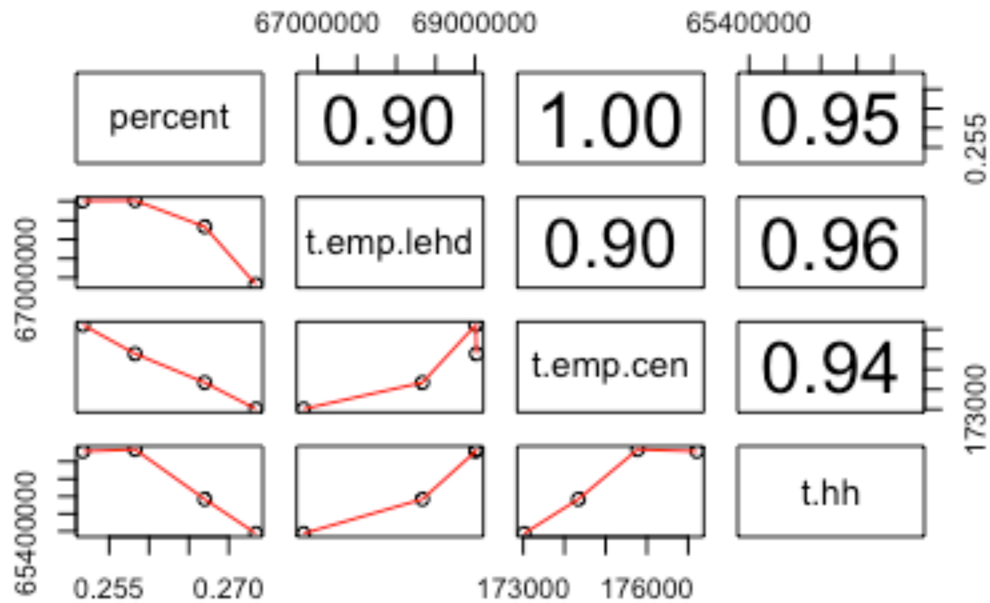

Figure 42: Scatterplot and Correlation Matrix for the Low Income Group

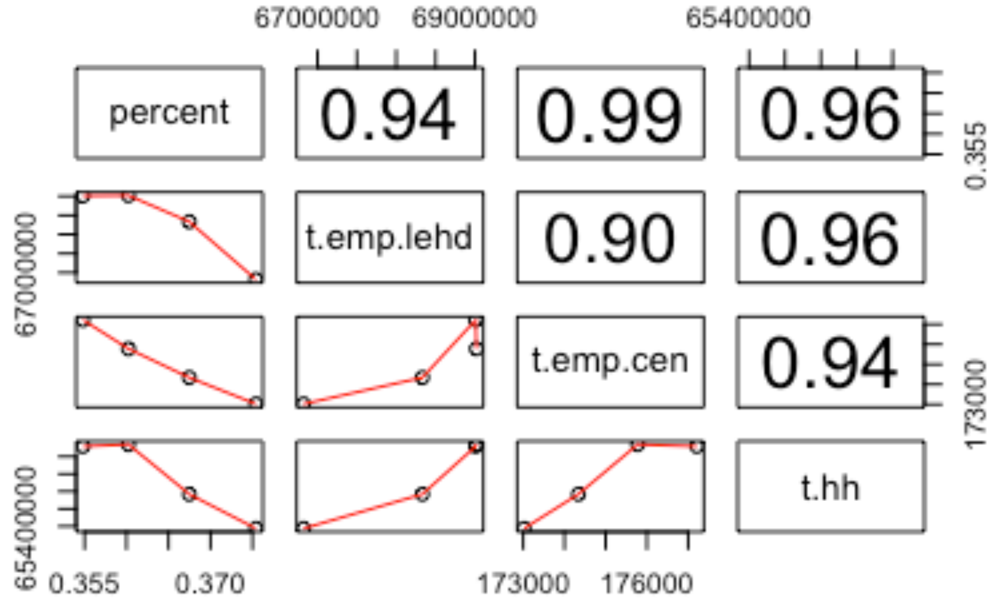

Figure 43: Scatterplot and Correlation Matrix for the Middle Income Group

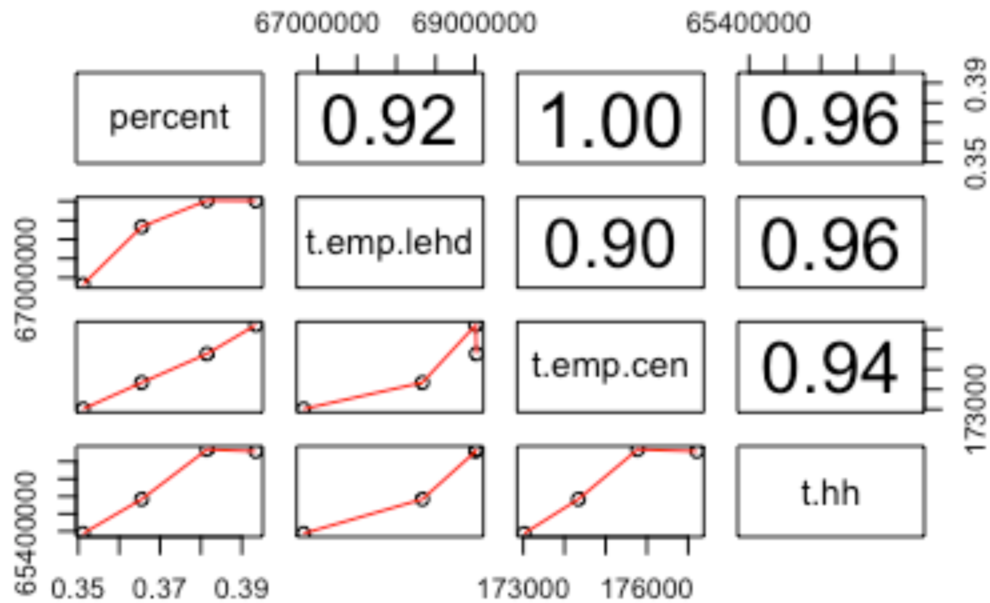

Figure 44: Scatterplot and Correlation Matrix for the High Income Group

Table 22: Model Results for Middle Income Earners Across Multiple Definitions of Middle Class

	ACS 50-150K	ACS 35-150K	ACS 50-200K	ACS 35-200K	LEHD
	1	2	3	4	5
Intercept	.33***	.50***	.35***	.52***	.42***
	(.02)	(.02)	(.02)	(.02)	(.01)
Employment Density	0.00***	0.00***	0.00***	0.00***	-0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
F.I.R.E.	.60*	.57*	.66*	.63*	.11
	(.25)	(.25)	(.28)	(.27)	(.19)
Manufacturing	.06	.10*	.01	.05	.19***
	(.05)	(.05)	(.05)	(.05)	(.04)
Management	.10	-.13	.24	.01	-1.10***
	(.39)	(.38)	(.43)	(.41)	(.29)
Observations	281	281	281	281	281
Akaike Inf. Crit.	-850.00	-867.00	-790.00	-820.00	-1,016.00

Notes: *P < .05; **P < .01; ***P < .001

APPENDIX B

REGRESSION MODEL TABLES

Table 23: Cusp Model Coefficients with Timberlake's Polarization as the Dependent Variable and F.I.R.E as the Control Parameter

	Timberlake (Scaled and Center)			
	1	2	3	4
Intercept	-.07***	-.07***	-.07***	-.09***
	(.02)	(.02)	(.02)	(.02)
Timberlake Squared	-.01	-.01	-.01	-0.00
	(.03)	(.03)	(.03)	(.03)
Timberlake Cubed	.01	.01	.01	.02
	(.01)	(.01)	(.01)	(.01)
F.I.R.E. Centrality		-.02	-.02	-.01
		(.01)	(.01)	(.01)
F.I.R.E. Centrality Velocity			.03	
			(.02)	
Timberlake				-.10***
				(.03)
Timberlake F.I.R.E. Interaction				-.03*
				(.02)
Observations	2,379	2,379	2,379	2,379
Log Likelihood	-2,160.00	-2,162.00	-2,164.00	-2,158.00
Akaike Inf. Crit.	4,334.00	4,341.00	4,347.00	4,335.00
Bayesian Inf. Crit.	4,375.00	4,387.00	4,398.00	4,393.00
Notes:	*P < .05			
	**P < .01			
	***P < .001			

Table 24: Cusp Model Coefficients with Timberlake's Polarization as the Dependent Variable and Eigenvector as the Control Parameter

	Timberlake (Scaled and Center)			
	1	2	3	4
Intercept	-.11***	-.11***	-.11***	-.13***
	(.02)	(.02)	(.02)	(.02)
Timberlake Squared	-.01	-.01	-.01	-.02
	(.03)	(.03)	(.03)	(.03)
Timberlake Cubed	.01	.01	.01	.03*
	(.01)	(.01)	(.01)	(.01)
Eigenvector Centrality		-.02	-.02	-.01
		(.01)	(.01)	(.01)
Eigenvector Centrality Velocity			.01	
			(.02)	
Timberlake				-.13***
				(.03)
Timberlake Eigenvector Interaction				-.02
				(.02)
Observations	1,829	1,829	1,829	1,829
Log Likelihood	-1,627.00	-1,629.00	-1,632.00	-1,623.00
Akaike Inf. Crit.	3,267.00	3,273.00	3,281.00	3,266.00
Bayesian Inf. Crit.	3,306.00	3,318.00	3,331.00	3,322.00
Notes:	*P < .05			
	**P < .01			
	***P < .001			

Table 25: Cusp Model Coefficients with Timberlake's Polarization as the Dependent Variable and In-Degree as the Control Parameter

	Timberlake (Scaled and Center)			
	1	2	3	4
Intercept	-.14***	-.14***	-.14***	-.16***
	(.02)	(.02)	(.02)	(.02)
Timberlake Squared	.01	.01	.01	.01
	(.03)	(.03)	(.03)	(.03)
Timberlake Cubed	0.00	0.00	0.00	.03*
	(.01)	(.01)	(.01)	(.01)
In-Degree Centrality		-.01	-.01	.01
		(.02)	(.02)	(.02)
In-Degree Centrality Velocity			.03	
			(.02)	
Timberlake				-.15***
				(.03)
Timberlake In-Degree Interaction				-.03
				(.02)
Observations	1,581	1,581	1,581	1,581
Log Likelihood	-1,371.00	-1,374.00	-1,376.00	-1,364.00
Akaike Inf. Crit.	2,756.00	2,764.00	2,770.00	2,747.00
Bayesian Inf. Crit.	2,793.00	2,807.00	2,819.00	2,801.00
Notes:	*P < .05			
	**P < .01			
	***P < .001			

Table 26: Cusp Model Coefficients with Timberlake's Polarization as the Dependent Variable and Out-Degree as the Control Parameter

	Timberlake (Scaled and Center)			
	1	2	3	4
Intercept	-.17***	-.17***	-.17***	-.20***
	(.04)	(.04)	(.04)	(.04)
Timberlake Squared	-.03	-.03	-.03	-.05
	(.06)	(.07)	(.06)	(.07)
Timberlake Cubed	.02	.02	.02	.06*
	(.02)	(.02)	(.02)	(.03)
Out-Degree Centrality		-.01	-.01	.01
		(.03)	(.03)	(.03)
Out-Degree Centrality Velocity			.07	
			(.05)	
Timberlake				-.23***
				(.06)
Timberlake Out-Degree Interaction				0.00
				(.03)
Observations	399	399	399	399
Log Likelihood	-350.00	-352.00	-354.00	-349.00
Akaike Inf. Crit.	714.00	721.00	725.00	718.00
Bayesian Inf. Crit.	742.00	753.00	761.00	758.00
Notes:	*P < .05			
	**P < .01			
	***P < .001			

Table 27: Cusp Model Coefficients with Timberlake's Polarization as the Dependent Variable and Betweenness as the Control Parameter

	Timberlake (Scaled and Center)			
	1	2	3	4
Intercept	-.17***	-.17***	-.17***	-.19***
	(.04)	(.04)	(.04)	(.04)
Timberlake Squared	-.02	-.03	-.02	-.05
	(.06)	(.06)	(.06)	(.06)
Timberlake Cubed	.01	.02	.01	.05*
	(.02)	(.02)	(.02)	(.02)
Betweenness Centrality		-.04	-.04	-.04
		(.03)	(.03)	(.03)
Betweenness Centrality Velocity			.09*	
			(.04)	
Timberlake				-.18***
				(.05)
Timberlake Betweenness Interaction				.03
				(.03)
Observations	455	455	455	455
Log Likelihood	-397.00	-399.00	-398.00	-397.00
Akaike Inf. Crit.	808.00	814.00	815.00	813.00
Bayesian Inf. Crit.	837.00	846.00	852.00	854.00
Notes:	*P < .05 **P < .01 ***P < .001			

Table 28: Cusp Model Coefficients with Middle Income Earners as the Dependent Variable and F.I.R.E. as the Control Parameter

	Middle Income (Scaled and Center)			
	1	2	3	4
Intercept	-.30***	-.30***	-.30***	-.31***
	(.01)	(.01)	(.01)	(.01)
Middle Income Squared	0.00	0.00	0.00	0.00
	(.01)	(.01)	(.01)	(.01)
Middle Income Cubed	-.01	-.01	-.01	.02
	(.01)	(.01)	(.01)	(.01)
F.I.R.E. Centrality		0.00	0.00	.01
		(.01)	(.01)	(.01)
F.I.R.E. Centrality Velocity			-.01	
			(.01)	
Middle Income				-.05**
				(.02)
Middle Income F.I.R.E. Interaction				.01
				(.01)
Observations	2,379	2,379	2,379	2,379
Log Likelihood	-671.00	-674.00	-678.00	-676.00
Akaike Inf. Crit.	1,355.00	1,365.00	1,374.00	1,372.00
Bayesian Inf. Crit.	1,395.00	1,411.00	1,425.00	1,430.00
Notes:	*P < .05			
	**P < .01			
	***P < .001			

Table 29: Cusp Model Coefficients with Middle Income Earners as the Dependent Variable and Eignvector as the Control Parameter

	Middle Income (Scaled and Center)			
	1	2	3	4
Intercept	-.31***	-.31***	-.31***	-.31***
	(.01)	(.01)	(.01)	(.01)
Middle Income Squared	0.00	0.00	0.00	-0.00
	(.01)	(.01)	(.01)	(.01)
Middle Income Cubed	-.01	-.01	-.01	.04**
	(.01)	(.01)	(.01)	(.01)
Eigenvector Centrality		.01	.01	.02*
		(.01)	(.01)	(.01)
Eigenvector Centrality Velocity			.02	
			(.01)	
Middle Income				-.08***
				(.02)
Middle Income Eigenvector Interaction				-0.00
				(.01)
Observations	1,829	1,829	1,829	1,829
Log Likelihood	-302.00	-304.00	-306.00	-300.00
Akaike Inf. Crit.	617.00	624.00	630.00	621.00
Bayesian Inf. Crit.	656.00	669.00	680.00	676.00
Notes:	*P < .05			
	**P < .01			
	***P < .001			

Table 30: Cusp Model Coefficients with Middle Income Earners as the Dependent Variable and In-Degree as the Control Parameter

	Middle Income (Scaled and Center)			
	1	2	3	4
Intercept	-.31***	-.31***	-.31***	-.32***
	(.01)	(.01)	(.01)	(.01)
Middle Income Squared	-0.00	-0.00	-0.00	-0.00
	(.01)	(.01)	(.01)	(.01)
Middle Income Cubed	-.01	-.01	-.01	.05***
	(.01)	(.01)	(.01)	(.01)
In-Degree Centrality		0.00	0.00	.01
		(.01)	(.01)	(.01)
In-Degree Centrality Velocity			.01	
			(.01)	
Middle Income				-.09***
				(.02)
Middle Income In-Degree Interaction				-0.00
				(.01)
Observations	1,581	1,581	1,581	1,581
Log Likelihood	-180.00	-184.00	-186.00	-178.00
Akaike Inf. Crit.	374.00	383.00	391.00	377.00
Bayesian Inf. Crit.	411.00	426.00	439.00	431.00
Notes:	*P < .05 **P < .01 ***P < .001			

Table 31: Cusp Model Coefficients with Middle Income Earners as the Dependent Variable and Out-Degree as the Control Parameter

	Middle Income (Scaled and Center)			
	1	2	3	4
Intercept	-.32***	-.32***	-.32***	-.33***
	(.02)	(.02)	(.02)	(.02)
Middle Income Squared	-0.00	-0.00	-0.00	.01
	(.02)	(.02)	(.02)	(.02)
Middle Income Cubed	-.02	-.01	-.02	.02
	(.01)	(.01)	(.01)	(.02)
Out-Degree Centrality		-.01	-.01	-.01
		(.01)	(.01)	(.01)
Out-Degree Centrality Velocity			.04*	
			(.02)	
Middle Income				-.05
				(.03)
Middle Income Out-Degree Interaction				-.03*
				(.02)
Observations	399	399	399	399
Log Likelihood	45.00	42.00	42.00	40.00
Akaike Inf. Crit.	-76.00	-68.00	-66.00	-59.00
Bayesian Inf. Crit.	-49.00	-36.00	-30.00	-19.00
Notes:	*P < .05			
	**P < .01			
	***P < .001			

Table 32: Cusp Model Coefficients with Middle Income Earners as the Dependent Variable and Betweenness as the Control Parameter

	Middle Income (Scaled and Center)			
	1	2	3	4
Intercept	-.33***	-.33***	-.33***	-.33***
	(.01)	(.01)	(.01)	(.01)
Middle Income Squared	.01	.01	.01	.01
	(.02)	(.02)	(.02)	(.02)
Middle Income Cubed	-.01	-.01	-.01	.01
	(.01)	(.01)	(.01)	(.02)
Betweenness Centrality		-0.00	-0.00	-0.00
		(.01)	(.01)	(.01)
Betweenness Centrality Velocity			.02	
			(.02)	
Middle Income				-.05
				(.03)
Middle Income Betweenness Interaction				-.05***
				(.01)
Observations	455	455	455	455
Log Likelihood	55.00	52.00	49.00	53.00
Akaike Inf. Crit.	-96.00	-87.00	-80.00	-86.00
Bayesian Inf. Crit.	-68.00	-54.00	-43.00	-45.00
Notes:	*P < .05			
	**P < .01			
	***P < .001			

Table 33: Cusp Model Coefficients with Low Income Blocks as the Dependent Variable and F.I.R.E. as the Control Parameter

	Low Income Blocks (Scaled and Center)			
	1	2	3	4
Intercept	-.22***	-.22***	-.22***	-.23***
	(.02)	(.02)	(.02)	(.02)
Low Income Blocks Squared	.04**	.04*	.04*	.05**
	(.02)	(.02)	(.02)	(.02)
Low Income Blocks Cubed	0.00	0.00	-0.00	-.02
	(.01)	(.01)	(.01)	(.01)
F.I.R.E. Centrality		.04**	.04**	.04**
		(.01)	(.01)	(.01)
F.I.R.E. Centrality Velocity			.06**	
			(.02)	
Low Income Blocks				.06*
				(.03)
Low Income Blocks F.I.R.E. Interaction				-.03
				(.02)
Observations	2,168	2,168	2,168	2,168
Log Likelihood	-1,840.00	-1,838.00	-1,837.00	-1,840.00
Akaike Inf. Crit.	3,694.00	3,693.00	3,692.00	3,700.00
Bayesian Inf. Crit.	3,733.00	3,738.00	3,744.00	3,757.00
Notes:	*P < .05			
	**P < .01			
	***P < .001			

Table 34: Cusp Model Coefficients with Low Income Blocks as the Dependent Variable and Eigenvector as the Control Parameter

	Low Income Blocks (Scaled and Center)			
	1	2	3	4
Intercept	-.22***	-.22***	-.22***	-.22***
	(.02)	(.02)	(.02)	(.02)
Low Income Blocks Squared	.03	.03	.03	.03
	(.02)	(.02)	(.02)	(.02)
Low Income Blocks Cubed	.01	.01	.01	-.01
	(.01)	(.01)	(.01)	(.01)
Eigenvector Centrality		.01	.01	0.00
		(.01)	(.01)	(.01)
Eigenvector Centrality Velocity			.03	
			(.02)	
Low Income Blocks				.06*
				(.03)
Low Income Blocks Eigenvector Interaction				-0.00
				(.02)
Observations	1,669	1,669	1,669	1,669
Log Likelihood	-1,397.00	-1,400.00	-1,402.00	-1,404.00
Akaike Inf. Crit.	2,807.00	2,816.00	2,822.00	2,827.00
Bayesian Inf. Crit.	2,845.00	2,859.00	2,871.00	2,881.00
Notes:	*P < .05			
	**P < .01			
	***P < .001			

Table 35: Cusp Model Coefficients with Low Income Blocks as the Dependent Variable and In-Degree as the Control Parameter

	Low Income Blocks (Scaled and Center)			
	1	2	3	4
Intercept	-.22***	-.22***	-.22***	-.23***
	(.02)	(.02)	(.02)	(.02)
Low Income Blocks Squared	.03	.03	.03	.04*
	(.02)	(.02)	(.02)	(.02)
Low Income Blocks Cubed	.01	.01	.01	-.03
	(.01)	(.01)	(.01)	(.02)
In-Degree Centrality		.02	.02	.02
		(.02)	(.02)	(.02)
In-Degree Centrality Velocity			.01	
			(.02)	
Low Income Blocks				.09**
				(.03)
Low Income Blocks In-Degree Interaction				-.01
				(.02)
Observations	1,422	1,422	1,422	1,422
Log Likelihood	-1,155.00	-1,157.00	-1,160.00	-1,159.00
Akaike Inf. Crit.	2,324.00	2,330.00	2,338.00	2,337.00
Bayesian Inf. Crit.	2,361.00	2,372.00	2,385.00	2,390.00
Notes:	*P < .05			
	**P < .01			
	***P < .001			

Table 36: Cusp Model Coefficients with Low Income Blocks as the Dependent Variable and Out-Degree as the Control Parameter

	Low Income Blocks (Scaled and Center)			
	1	2	3	4
Intercept	-.21***	-.21***	-.21***	-.23***
	(.03)	(.03)	(.03)	(.03)
Low Income Blocks Squared	-.04	-.03	-.03	-0.00
	(.05)	(.05)	(.05)	(.05)
Low Income Blocks Cubed	.03	.03	.03	-.03
	(.03)	(.03)	(.03)	(.05)
Out-Degree Centrality		.05	.05	.05
		(.03)	(.03)	(.03)
Out-Degree Centrality Velocity			.05	
			(.04)	
Low Income Blocks				.12
				(.07)
Low Income Blocks Out-Degree Interaction				-.04
				(.05)
Observations	371	371	371	371
Log Likelihood	-283.00	-284.00	-286.00	-287.00
Akaike Inf. Crit.	581.00	585.00	590.00	593.00
Bayesian Inf. Crit.	608.00	616.00	625.00	632.00
Notes:	*P < .05 **P < .01 ***P < .001			

Table 37: Cusp Model Coefficients with Low Income Blocks as the Dependent Variable and Betweenness as the Control Parameter

	Low Income Blocks (Scaled and Center)			
	1	2	3	4
Intercept	-.22***	-.23***	-.23***	-.24***
	(.03)	(.03)	(.03)	(.03)
Low Income Blocks Squared	-.02	-.01	-.01	.01
	(.05)	(.05)	(.05)	(.05)
Low Income Blocks Cubed	.03	.03	.03	-.05
	(.03)	(.03)	(.03)	(.04)
Betweenness Centrality		.05	.05	.05
		(.03)	(.03)	(.03)
Betweenness Centrality Velocity			.09*	
			(.04)	
Low Income Blocks				.15*
				(.06)
Low Income Blocks Betweenness Interaction				-.03
				(.04)
Observations	427	427	427	427
Log Likelihood	-324.00	-325.00	-325.00	-326.00
Akaike Inf. Crit.	663.00	667.00	668.00	673.00
Bayesian Inf. Crit.	691.00	699.00	704.00	713.00
Notes:	*P < .05 **P < .01 ***P < .001			

Table 38: Cusp Model Coefficients with Middle Income Blocks as the Dependent Variable and F.I.R.E. as the Control Parameter

	Middle Income Blocks (Scaled and Center)			
	1	2	3	4
Intercept	-.20***	-.20***	-.20***	-.20***
	(.02)	(.02)	(.02)	(.02)
Middle Income Blocks Squared	0.00	0.00	0.00	0.00
	(.02)	(.02)	(.02)	(.02)
Middle Income Blocks Cubed	.01	.01	.01	.01
	(.01)	(.01)	(.01)	(.01)
F.I.R.E. Centrality		.07***	.07***	.07***
		(.01)	(.01)	(.01)
F.I.R.E. Centrality Velocity			.04*	
			(.02)	
Middle Income Blocks				0.00
				(.03)
Middle Income Blocks F.I.R.E. Interaction				-.03
				(.02)
Observations	2,170	2,170	2,170	2,170
Log Likelihood	-1,894.00	-1,884.00	-1,885.00	-1,889.00
Akaike Inf. Crit.	3,801.00	3,785.00	3,788.00	3,797.00
Bayesian Inf. Crit.	3,841.00	3,830.00	3,840.00	3,854.00
Notes:	*P < .05			
	**P < .01			
	***P < .001			

Table 39: Cusp Model Coefficients with Middle Income Blocks as the Dependent Variable and Eigenvector as the Control Parameter

	Middle Income Blocks (Scaled and Center)			
	1	2	3	4
Intercept	-.21***	-.21***	-.21***	-.21***
	(.02)	(.02)	(.02)	(.02)
Middle Income Blocks Squared	.01	.01	.01	.01
	(.02)	(.02)	(.02)	(.02)
Middle Income Blocks Cubed	.01	.01	.01	-.02
	(.01)	(.01)	(.01)	(.01)
Eigenvector Centrality		-.01	-.01	-.01
		(.01)	(.01)	(.01)
Eigenvector Centrality Velocity			-.03	
			(.02)	
Middle Income Blocks				.06
				(.03)
Middle Income Blocks Eigenvector Interaction				.02
				(.02)
Observations	1,673	1,673	1,673	1,673
Log Likelihood	-1,417.00	-1,420.00	-1,422.00	-1,423.00
Akaike Inf. Crit.	2,847.00	2,855.00	2,862.00	2,866.00
Bayesian Inf. Crit.	2,885.00	2,899.00	2,910.00	2,920.00
Notes:	*P < .05 **P < .01 ***P < .001			

Table 40: Cusp Model Coefficients with Middle Income Blocks as the Dependent Variable and In-Degree as the Control Parameter

	Middle Income Blocks (Scaled and Center)			
	1	2	3	4
Intercept	-.22***	-.22***	-.22***	-.22***
	(.02)	(.02)	(.02)	(.02)
Middle Income Blocks Squared	.02	.02	.02	.02
	(.02)	(.02)	(.02)	(.02)
Middle Income Blocks Cubed	.01	.01	.01	-.02
	(.01)	(.01)	(.01)	(.02)
In-Degree Centrality		-.02	-.02	-.03
		(.02)	(.02)	(.02)
In-Degree Centrality Velocity			-.01	
			(.02)	
Middle Income Blocks				.06*
				(.03)
Middle Income Blocks In-Degree Interaction				.01
				(.02)
Observations	1,425	1,425	1,425	1,425
Log Likelihood	-1,179.00	-1,181.00	-1,184.00	-1,185.00
Akaike Inf. Crit.	2,372.00	2,379.00	2,386.00	2,389.00
Bayesian Inf. Crit.	2,409.00	2,421.00	2,433.00	2,442.00
Notes:	*P < .05			
	**P < .01			
	***P < .001			

Table 41: Cusp Model Coefficients with Middle Income Blocks as the Dependent Variable and Out-Degree as the Control Parameter

	Middle Income Blocks (Scaled and Center)			
	1	2	3	4
Intercept	-.25***	-.25***	-.25***	-.26***
	(.03)	(.03)	(.03)	(.03)
Middle Income Blocks Squared	.01	.01	.01	.02
	(.04)	(.04)	(.04)	(.04)
Middle Income Blocks Cubed	.01	.01	.01	-.04
	(.02)	(.02)	(.02)	(.03)
Out-Degree Centrality		-.02	-.02	-.03
		(.03)	(.03)	(.03)
Out-Degree Centrality Velocity			.01	
			(.04)	
Middle Income Blocks				.12
				(.06)
Middle Income Blocks Out-Degree Interaction				-.01
				(.04)
Observations	371	371	371	371
Log Likelihood	-279.00	-281.00	-283.00	-283.00
Akaike Inf. Crit.	572.00	578.00	585.00	587.00
Bayesian Inf. Crit.	599.00	609.00	620.00	626.00
Notes:	*P < .05			
	**P < .01			
	***P < .001			

Table 42: Cusp Model Coefficients with Middle Income Blocks as the Dependent Variable and Betweenness as the Control Parameter

	Middle Income Blocks (Scaled and Center)			
	1	2	3	4
Intercept	-.26***	-.26***	-.26***	-.27***
	(.03)	(.03)	(.03)	(.03)
Middle Income Blocks Squared	.02	.02	.02	.03
	(.04)	(.04)	(.04)	(.04)
Middle Income Blocks Cubed	.01	.01	.01	-.04
	(.02)	(.02)	(.02)	(.03)
Betweenness Centrality		.03	.03	.04
		(.03)	(.03)	(.03)
Betweenness Centrality Velocity			.05	
			(.04)	
Middle Income Blocks				.11*
				(.05)
Middle Income Blocks Betweenness Interaction				-.02
				(.04)
Observations	427	427	427	427
Log Likelihood	-305.00	-307.00	-308.00	-309.00
Akaike Inf. Crit.	624.00	630.00	634.00	638.00
Bayesian Inf. Crit.	652.00	662.00	671.00	679.00
Notes:	*P < .05			
	**P < .01			
	***P < .001			

Table 43: Cusp Model Coefficients with High Income Blocks as the Dependent Variable and F.I.R.E. as the Control Parameter

	High Income Blocks (Scaled and Center)			
	1	2	3	4
Intercept	.16***	.15***	.15***	.16***
	(.02)	(.02)	(.02)	(.02)
High Income Blocks Squared	-.08***	-.08***	-.08***	-.08***
	(.02)	(.02)	(.02)	(.02)
High Income Blocks Cubed	-.02***	-.02**	-.02**	-0.00
	(.01)	(.01)	(.01)	(.01)
F.I.R.E. Centrality		.08***	.08***	.06***
		(.01)	(.01)	(.02)
F.I.R.E. Centrality Velocity			.05*	
			(.02)	
High Income Blocks				-.06*
				(.03)
High Income Blocks F.I.R.E. Interaction				.05**
				(.02)
Observations	2,168	2,168	2,168	2,168
Log Likelihood	-2,020.00	-2,009.00	-2,010.00	-2,008.00
Akaike Inf. Crit.	4,053.00	4,035.00	4,038.00	4,036.00
Bayesian Inf. Crit.	4,093.00	4,080.00	4,089.00	4,093.00
Notes:	*P < .05 **P < .01 ***P < .001			

Table 44: Cusp Model Coefficients with High Income Blocks as the Dependent Variable and Eigenvector as the Control Parameter

	High Income Blocks (Scaled and Center)			
	1	2	3	4
Intercept	.16***	.16***	.16***	.17***
	(.02)	(.02)	(.02)	(.02)
High Income Blocks Squared	-.09***	-.09***	-.09***	-.10***
	(.02)	(.02)	(.02)	(.02)
High Income Blocks Cubed	-.03**	-.03**	-.03**	0.00
	(.01)	(.01)	(.01)	(.01)
Eigenvector Centrality		.02	.02	.02
		(.02)	(.02)	(.02)
Eigenvector Centrality Velocity			.03	
			(.02)	
High Income Blocks				-.08*
				(.03)
High Income Blocks Eigenvector Interaction				.03
				(.02)
Observations	1,669	1,669	1,669	1,669
Log Likelihood	-1,547.00	-1,549.00	-1,551.00	-1,551.00
Akaike Inf. Crit.	3,107.00	3,114.00	3,120.00	3,122.00
Bayesian Inf. Crit.	3,145.00	3,158.00	3,169.00	3,176.00
Notes:	*P < .05			
	**P < .01			
	***P < .001			

Table 45: Cusp Model Coefficients with High Income Blocks as the Dependent Variable and In-Degree as the Control Parameter

	High Income Blocks (Scaled and Center)			
	1	2	3	4
Intercept	.17***	.17***	.17***	.17***
	(.02)	(.02)	(.02)	(.02)
High Income Blocks Squared	-.10***	-.10***	-.10***	-.10***
	(.02)	(.02)	(.02)	(.02)
High Income Blocks Cubed	-.03**	-.03**	-.03**	0.00
	(.01)	(.01)	(.01)	(.02)
In-Degree Centrality		.03	.03	.02
		(.02)	(.02)	(.02)
In-Degree Centrality Velocity			.02	
			(.03)	
High Income Blocks				-.09*
				(.03)
High Income Blocks In-Degree Interaction				.03
				(.02)
Observations	1,421	1,421	1,421	1,421
Log Likelihood	-1,306.00	-1,308.00	-1,310.00	-1,309.00
Akaike Inf. Crit.	2,627.00	2,632.00	2,638.00	2,638.00
Bayesian Inf. Crit.	2,664.00	2,674.00	2,686.00	2,690.00
Notes:	*P < .05			
	**P < .01			
	***P < .001			

Table 46: Cusp Model Coefficients with High Income Blocks as the Dependent Variable and Out-Degree as the Control Parameter

	High Income Blocks (Scaled and Center)			
	1	2	3	4
Intercept	.23***	.22***	.22***	.23***
	(.04)	(.04)	(.04)	(.04)
High Income Blocks Squared	-.13***	-.13***	-.13***	-.13***
	(.04)	(.04)	(.04)	(.04)
High Income Blocks Cubed	-.05**	-.05**	-.05**	-.02
	(.02)	(.02)	(.02)	(.03)
Out-Degree Centrality		.06	.06	.05
		(.03)	(.03)	(.03)
Out-Degree Centrality Velocity			-0.00	
			(.05)	
High Income Blocks				-.08
				(.06)
High Income Blocks Out-Degree Interaction				.03
				(.04)
Observations	371	371	371	371
Log Likelihood	-313.00	-313.00	-316.00	-317.00
Akaike Inf. Crit.	639.00	643.00	649.00	653.00
Bayesian Inf. Crit.	667.00	674.00	684.00	692.00
Notes:	*P < .05			
	**P < .01			
	***P < .001			

Table 47: Cusp Model Coefficients with High Income Blocks as the Dependent Variable and Betweenness as the Control Parameter

	High Income Blocks (Scaled and Center)			
	1	2	3	4
Intercept	.24***	.22***	.22***	.22***
	(.04)	(.04)	(.04)	(.04)
High Income Blocks Squared	-.15***	-.14***	-.14***	-.15***
	(.04)	(.04)	(.04)	(.04)
High Income Blocks Cubed	-.04*	-.04*	-.04*	.01
	(.02)	(.02)	(.02)	(.03)
Betweenness Centrality		.07*	.08*	.07*
		(.03)	(.03)	(.03)
Betweenness Centrality Velocity			.07	
			(.04)	
High Income Blocks				-.11
				(.06)
High Income Blocks Betweenness Interaction				.07
				(.04)
Observations	427	427	427	427
Log Likelihood	-370.00	-369.00	-370.00	-370.00
Akaike Inf. Crit.	753.00	754.00	758.00	760.00
Bayesian Inf. Crit.	781.00	786.00	794.00	800.00
Notes:	*P < .05			
	**P < .01			
	***P < .001			

Table 48: Cusp Model Coefficients with Gentrified Blocks as the Dependent Variable and F.I.R.E. as the Control Parameter

	Gentrified Blocks (Scaled and Center)			
	1	2	3	4
Intercept	.02	.01	.02	.03
	(.02)	(.02)	(.02)	(.02)
Gentrified Blocks Squared	.01	.01	.01	-0.00
	(.02)	(.02)	(.02)	(.02)
Gentrified Blocks Cubed	-.01	-.01	-0.00	.03*
	(.01)	(.01)	(.01)	(.02)
F.I.R.E. Centrality		.12***	.12***	.12***
		(.02)	(.02)	(.02)
F.I.R.E. Centrality Velocity			.04	
			(.03)	
Gentrified Blocks				-.10**
				(.03)
Gentrified Blocks F.I.R.E. Interaction				-.01
				(.02)
Observations	1,903	1,903	1,903	1,903
Log Likelihood	-1,965.00	-1,944.00	-1,945.00	-1,944.00
Akaike Inf. Crit.	3,945.00	3,903.00	3,908.00	3,908.00
Bayesian Inf. Crit.	3,984.00	3,948.00	3,958.00	3,963.00

Notes: *P < .05
**P < .01
***P < .001

Table 49: Cusp Model Coefficients with Gentrified Blocks as the Dependent Variable and Eigenvector as the Control Parameter

	Gentrified Blocks (Scaled and Center)			
	1	2	3	4
Intercept	.01	.01	.01	.04
	(.02)	(.02)	(.02)	(.02)
Gentrified Blocks Squared	.02	.02	.01	-0.00
	(.03)	(.03)	(.03)	(.03)
Gentrified Blocks Cubed	-.01	-.01	-.01	.05*
	(.01)	(.01)	(.01)	(.02)
Eigenvector Centrality		.06**	.06**	.06**
		(.02)	(.02)	(.02)
Eigenvector Centrality Velocity			.13***	
			(.03)	
Gentrified Blocks				-.15***
				(.04)
Gentrified Blocks Eigenvector Interaction				-0.00
				(.03)
Observations	1,463	1,463	1,463	1,463
Log Likelihood	-1,494.00	-1,493.00	-1,484.00	-1,490.00
Akaike Inf. Crit.	3,003.00	3,002.00	2,986.00	3,000.00
Bayesian Inf. Crit.	3,040.00	3,044.00	3,034.00	3,053.00
Notes:	*P < .05			
	**P < .01			
	***P < .001			

Table 50: Cusp Model Coefficients with Gentrified Blocks as the Dependent Variable and In-Degree as the Control Parameter

	Gentrified Blocks (Scaled and Center)			
	1	2	3	4
Intercept	.02	.02	.03	.05*
	(.02)	(.02)	(.02)	(.03)
Gentrified Blocks Squared	.01	.02	.01	-0.00
	(.03)	(.03)	(.03)	(.03)
Gentrified Blocks Cubed	-.01	-.01	-.01	.04*
	(.02)	(.01)	(.01)	(.02)
In-Degree Centrality		.11***	.11***	.11***
		(.02)	(.02)	(.02)
In-Degree Centrality Velocity			.04	
			(.03)	
Gentrified Blocks				-.15***
				(.04)
Gentrified Blocks In-Degree Interaction				-.02
				(.03)
Observations	1,246	1,246	1,246	1,246
Log Likelihood	-1,268.00	-1,257.00	-1,259.00	-1,255.00
Akaike Inf. Crit.	2,549.00	2,531.00	2,536.00	2,530.00
Bayesian Inf. Crit.	2,585.00	2,572.00	2,582.00	2,581.00
Notes:	*P < .05			
	**P < .01			
	***P < .001			

Table 51: Cusp Model Coefficients with Gentrified Blocks as the Dependent Variable and Out-Degree as the Control Parameter

	Gentrified Blocks (Scaled and Center)			
	1	2	3	4
Intercept	.05	.05	.06	.13**
	(.05)	(.05)	(.05)	(.05)
Gentrified Blocks Squared	0.00	-.01	-.01	-.02
	(.07)	(.07)	(.07)	(.07)
Gentrified Blocks Cubed	-.02	-.02	-.02	.10*
	(.04)	(.04)	(.04)	(.05)
Out-Degree Centrality		.13**	.13**	.11*
		(.04)	(.04)	(.05)
Out-Degree Centrality Velocity			.06	
			(.06)	
Gentrified Blocks				-.35***
				(.09)
Gentrified Blocks Out-Degree Interaction				.02
				(.06)
Observations	324	324	324	324
Log Likelihood	-336.00	-333.00	-334.00	-329.00
Akaike Inf. Crit.	686.00	682.00	687.00	678.00
Bayesian Inf. Crit.	712.00	712.00	721.00	716.00
Notes:	*P < .05			
	**P < .01			
	***P < .001			

Table 52: Cusp Model Coefficients with Gentrified Blocks as the Dependent Variable and Betweenness as the Control Parameter

	Gentrified Blocks (Scaled and Center)			
	1	2	3	4
Intercept	.05	.04	.03	.11*
	(.04)	(.04)	(.04)	(.05)
Gentrified Blocks Squared	0.00	-0.00	.01	-.01
	(.07)	(.07)	(.07)	(.07)
Gentrified Blocks Cubed	-.02	-.02	-.02	.10*
	(.04)	(.04)	(.04)	(.05)
Betweenness Centrality		.08*	.07	.06
		(.04)	(.04)	(.04)
Betweenness Centrality Velocity			.15**	
			(.05)	
Gentrified Blocks				-.37***
				(.08)
Gentrified Blocks Betweenness Interaction				.07
				(.06)
Observations	373	373	373	373
Log Likelihood	-384.00	-385.00	-382.00	-378.00
Akaike Inf. Crit.	782.00	785.00	783.00	777.00
Bayesian Inf. Crit.	810.00	816.00	818.00	816.00
Notes:	*P < .05 **P < .01 ***P < .001			

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